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Drivers of Wearable Computing Adoption: An Empirical Study of Success Factors Including IT Security and Consumer Behaviour-Related Aspects

by

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AUTHOR'S DECLARATION

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Graduate Committee.

Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

Relevant scientific seminars and conferences were regularly attended at which work was presented.

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Abstract

Drivers of Wearable Computing Adoption: An Empirical Study of Success Factors Including IT Security and Consumer Behaviour-Related Aspects

Lena Gribel

The recent advances in information technologies have dramatically changed the manner in which people understand, experience and use IT systems. Wearable computers are emerging new technologies in the evolution of mobile devices, which introduce a paradigm shift in the field of human computer-interaction. By equipping the user with computational capabilities, 'wearables' provide context-aware and seamlessly integrated on-the-fly computing across heterogeneous circumstances and irrespective of place and time. Not least the very promising market prospects for wearable devices imply various unprecedented business opportunities and a vast economic potential of these socio-technological gadgets. Nonetheless, analysis of the current market situation shows that the wearable computing sector is still a niche, characterised by low public awareness and a high level of turbulence and uncertainty. In view of the numerous efforts in the area of innovation, which failed due to a lack of consumer acceptance, it becomes clear that facilitation of acceptability is a key issue for entrepreneurship. However, up to now, there is only little scientific research on the acceptance of ubiquitous computing in general and, in particular, on the latent success factors of the wearable computing phenomenon. At the same time, it is also significant that personality variables have seldom been examined within the scope of Information Systems research. Therefore, the overall aim of this study is to deepen understanding of latent psychographic factors that lead to either acceptance or resistance towards wearable computing. Specifically, a new behavioural model is introduced, which extends the well-established Technology Acceptance Model (TAM) by explicitly incorporating a dispositional perspective into the conceptual framework.

By means of an extensive literature review that combines different streams of research, this thesis lays a theoretical substantiation of the study. Based on the findings from the conceptual work together with the results from an exploratory study, salient psychological factors are identified and integrated into a coherent system of hypotheses. The derived cause-effect model conceptualises the behavioural intention to use wearables as a consequence of cognitive beliefs and personality-related correlates. The validity of the structural model and its measurement instruments is empirically tested with the aid of a web-based survey that was distributed to a sample of over 500 participants from the target population, of which 474 cases were accepted. The results of the quantitative study identify the *perceived support of health and fitness* as well as the *perceived enhancement of personal abilities* as strongest individual-level drivers that affect the intention to use wearable technologies. On the contrary, *perceived privacy risk* was found to be a major barrier to adoption. Furthermore, the analysis of moderator effects shows that both the level of *personal innovativeness* and *past experience with wearables* indirectly influence benefit expectations. In other words, innovative individuals and those who are familiar with these technologies are more likely to develop positive attitudes towards the use of wearable devices.

The empirical findings not only contribute to the existing body of knowledge in Information Systems research, but also have several important implications for marketing practitioners. Given the dominance of cognitive beliefs in attitude formation, companies in the wearable sector should focus more on informative issues in their communication to educate consumers about the main benefits of wearables. For wearables to be perceived as useful, they should operate even more naturally and unobtrusively than preceding mobile innovations, what clearly reinforces the significance of human-centred design principles and an implicit human-computer interaction. Since the study findings reveal that potential breaches in data privacy represent the greatest IT security concern, vendors should aim at improving consumer attitudes towards their privacy practices. Moreover, considering that risk perceptions are heavily affected by trusting beliefs, building consumer trust appears to be key in reducing latent uncertainties and resistance to adoption. In view of the individual differences that were proved to be of behavioural relevance, it seems furthermore worthwhile to divide the consumer market psychographically into relevant personality profiles: In the case of wearable computing, especially consumers who score high on the trait of neuroticism will act as early adopters. By developing target-group oriented communication strategies, marketers may efficiently approach the key segment of current and prospective wearable computing users.

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List of Abbreviations

AVE	Average Variance Extracted
BFI	Big Five Inventory
BS	British Standard
BSI	British Standards Institution
BYOD	Bring Your Own Device
CAGR	Compound Annual Growth Rate
CB-SEM	Covariance-based Structural Equation Modeling
CIA	Confidentiality Integrity Availability
CMV	Common Method Variance
CPU	Central Processing Unit
DTPB	Decomposed Theory of Planned Behavior
e.g.	exempli gratia
EC	European Community
EEG	Electroencephalogram
EFA	Exploratory Factor Analysis
et al.	et alii
EV	eigenvalue
EV	Expectancy Value
ff.	pages following
FFM	Five Factor Model
GLS	Generalized Least Squares
HTMT	Heterotrait-Monotrait Ratio
i.e.	id est
ibid.	ibidem
ICH	Intelligence Compensation Hypothesis
ICT	Information and Communication Technology
IDT	Innovation Diffusion Theory
IEC	International Electrotechnical Commission

IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IPMA	Importance-Performance-Map Analysis
ISO	International Organization for Standardization
IT	Information Technology
MGA	Multigroup Analysis
ML	Maximum Likelihood
NFC	Need for Cognition
OLS	Ordinary Least Squares
p.	page
PC	Personal Computer
PCA	Principal Component Analysis
PII	Personal Involvement Inventory
PIN	Personal Identification Number
PLS	Partial Least Squares
PLSc	consistent PLS
R&D	Research and Development
SEM	Structural Equation Modeling
S-O-R	Stimulus-Organism-Response
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VAF	Variance Accounted For
VIF	Variance Inflation Factor
VR	Virtual Reality
WiFi	Wireless Fidelity
WLS	Weighted Least Squares

1 Introduction

The main purpose of this chapter is to provide an overview of the key issues associated with the subject of study. The chapter commences with an introduction of the research context. Next, the research aims and questions are established, followed by a brief outline of the thesis structure.

1.1 On the Increasing Significance of Wearable Computing Adoption

The exponential performance enhancement of microprocessors and miniature sensors as well as the significant advances in multiple other technology parameters, such as data transfer rates in wired and wireless networks, has led to an accelerating growth of computerisation. Particularly, the transition from encapsulated smart spaces to more interconnected and even invisible computing environments entails an increasing integration of sensing, communication, and computation into the physical world. This evolution opens up a wide range of fascinating innovations in information and communication technologies (ICT). Wearable computing is an emerging computing paradigm, which emphasises an omnipresent as well as unobtrusive mediation and augmentation of context-related information in real-time. As the demand for mobile applications in numerous aspects of both the consumer and enterprise realm grows, the ecosystem of intelligent wearable devices containing microchips, sensors, network technologies and software is steadily prospering. Correspondingly, the market intelligence firm Tractica (2016) predicts a market volume of up to 95.27 milliard U.S. dollars for the global wearable smart electronics industry by 2021.

Driven by this enormous economic potential of ‘smart wearware’, large consumer brand companies, such as Samsung, Apple, Siemens and Google, but also a variety of innovative start-ups engage in the rapid-growth wearable market by tapping new business segments and launching own wearable products. For instance, the ‘Pebble Technology Corporation’, which largely financed its business venture via crowdfunding, greatly succeeded with its e-paper based smartwatch (Smartwatch Group, 2015).

In the meantime, there is a high degree of product diversity in the area of wearable computers, ranging from smart wristwatches, glasses, jewelleries, headgears and e-textiles to digital contact lenses, consumer EEGs and even smart tattoos (Swan, 2012 p. 220-227; Titcomb, 2016). All these wearable products promise substantial efficiency gains on the end-user’s side by creating seamless and convenient access to critical electronics and information services. Given the added value through augmented reality applications and a more unobtrusive design in comparison to conventional hand-held devices, wearables are currently influencing a multitude of non-consumer niches including those in healthcare, education, transportation and manufacturing (Tehrani, et al., 2014; Amft, 2017). For instance, smart glasses are beneficial to heavy industry by providing interactive, hands-free manuals and up-to-the-minute information (Gartner, Inc., 2013a). The practical implications of such lightweight devices are far-reaching and, consequently, their application fields are expected to expand in scope and scale. An illustrative example in the field of medical education is Google Glass, which already has been successfully utilised to live stream surgical procedures for teaching purposes (Dolan, 2013; Chang, et al., 2016). From a cross-industry perspective, the Gartner Hype Cycle for emerging technologies shows that human augmentation (in the sense of

technology-enabled cognitive and physical improvements) is right at the beginning of the innovation trigger phase, which promises a high degree of competitive advantage over the next ten years (Panetta, 2017). This indicates the considerable impact wearable technologies might have not only on industry, but also on a variety of consumer sectors in the near term.

To date, highly specialised wearables in the field of personal health and wellness (i.e. fitness tracking wrist-bands such as FitBit Flex and Nike Fuelband) are the most established wearable devices (Nielsen, 2014; González, 2017). These electronics are designed for single use-cases, meeting the trend among consumers toward the 'quantified self' by offering purposeful functionality in vertical markets. However, despite the increasing application of other multifunction wearable systems in professional and industrial settings (e.g. smart glasses or smartwatches), the rate of adoption in mainstream markets is considered fairly low due to both an early stage of development and a yet unclear value proposition (Bajarin, 2013; Gartner, Inc., 2016). As a consequence, many companies have to face the dilemma that their wearable technology innovations still lack consumer acceptance (BI Intelligence, 2015). For instance, the sales numbers of Apple's smartwatch were far behind the forecast figures only three months after market launch (Arends, 2015). Since then, this branded product experienced a consecutive decline in shipments which could only be counteracted with the launch auf the Apple Watch Series 2 and 3 in 2017 (Canalys, 2018).

Surprisingly, up to now it is still largely unknown what between-subject factors might play a key role for mass market breakthrough of general-purpose wearables (Groopman, 2014; Briggs, 2014). From a rational point of view, the decision as to whether or not to employ a new technology depends primarily on its price and usefulness. However, consumers do not always act rationally and utility-maximising. Instead, their adoption behaviour heavily depends on psychographic characteristics like subjective beliefs, personal values and lifestyles (Buenaflor, et al., 2012 p. 579; Planing, 2014 p. 1). Therefore, identification of concrete socio-psychological antecedents of technology acceptance appears to be highly important for an effective customer approach. In regard to the current absence of product necessity and clear functional benefits of wearables, it seems also pivotal to ascertain motivational drivers of consumers' utility perception.

Furthermore, smart wearable products are associated with a number of specific challenges and adoption barriers. Along with typical acceptance inhibitors of mobile devices including price, battery life and ease of use, particularly information security concerns are vital (Lindström, 2007 p. 3-4; Rawassizadeh, et al., 2015). Although security and privacy technologies are evolving, wearable computers still pose severe privacy issues and threat scenarios (Zorz, 2014). Thus, the influence of consumers' security perception on usage intention should be examined too, so as to gain a holistic and comprehensive understanding of wearable technology acceptance. Taken together, this unique research context constitutes a promising field for the application of Information Systems and acceptance research. It may pave the ground for valuable insights into the area of innovation diffusion from a new perspective.

In light of the increasing importance of tiny, wireless-connected devices, it is noticeable that there is almost no research that goes beyond descriptive studies on wearable technology adoption. Existing explanatory models incorporate only partial aspects of attitude formation, as they seek to be as parsimonious as possible in a positivistic manner (e.g. Chuah, et al., 2016, or Rauschnabel, et al., 2015a). Moreover, research in the field of technology acceptance focusses mostly on traditional information technologies such as e-mail systems, electronic commerce

applications or online banking. These approaches capture merely a fraction of the relevant factors that might play a crucial role in the adoption of future information and communication technologies (Sharma, et al., 2014 p. 27). Consequently, they might suffice for their individual domains, but clearly fall short for investigating acceptance-enhancing factors of ultra-mobile devices in the evolving 'post-PC' era. However, a comprehensive understanding of the inter-individual adoption process is essential for a successful market launch and rapid diffusion of wearables.

It is also striking that there is generally a lack of systematic research on the significance of personality parameters in the context of Information Systems research (Zhou, et al., 2011 p. 545; Svendsen, et al., 2013 p. 323). Hence, this thesis combines theoretical assumptions and conceptual frameworks from different research streams including the fields of Information Systems (IS), consumer behaviour and personality psychology. Furthermore, available research studies on technology acceptance mostly tend to address factors of innovation success and therefore frequently neglect determinants that hinder the diffusion of new technologies. This phenomenon is due to a shortcoming in diffusion research referred to as the pro-innovation-bias, which implicates that innovations are adopted by all members of a given social system, ignoring either re-inventions or rejections (Rogers, 2010, p. 100). Especially the perceived risk associated with adopting a new technology is commonly considered a major reason for resistance to innovation (Ram, 1987 p. 208-212). Again, in a wearable computing context IT security risks render particularly important. At this point, it is remarkable that the well-established goals in information security have neither been analysed in detail from a consumer's perspective nor incorporated into existing models in the context of technology acceptance research. Therefore, the present research work also considers adoption inhibitors in terms of security-related aspects of IT.

In sum, this thesis contributes to theory by providing an empirical (i.e. observation-based) investigation of consumers' adoption behaviour towards emerging wearable technologies. As regards the research methodology, this study takes a sequential mixed-methods approach combining both qualitative and quantitative data, yet with a bias towards quantitative methods. A justification for the methodological choices as well as the details of the research processes employed are presented at each stage of this study. In a first step, important acceptance factors of wearable computing are identified and conceptualised based on literature review and in-depth expert interviews. Drawing on the proposed theoretical concepts from the qualitative research stage, a novel structural model for explaining and predicting adoption behaviour in the relevant markets, the Wearable Technology Acceptance Model (Wearable TAM), is successively derived and introduced. For theory verification purposes, this newly developed model is then validated within the main quantitative study by means of a large-scale Internet survey. Since the study focusses on latent (i.e. not directly measurable) individual-level factors that influence the adoption decision, structural equation modeling is employed as a multivariate data analysis technique for assessing the reliability and validity of model measures. Building on long-established theories of attitude and innovation acceptance, the Wearable TAM seeks to provide a comprehensive picture of both intrinsic adopter-related and extrinsic product-related acceptance drivers. It conceptualises the individual intention to use wearables as a multicausal, dependent variable that serves as a proxy of actual acceptance behaviour. From a factor-analytical perspective, the research model inherently adheres to an exploratory, prediction-oriented approach: By empirically analysing the patterns of correlations among a set of hypothesised constructs, this study aims at deriving concrete managerial recommendations on how to increase consumers' willingness to adopt wearable computing. Finally, a

profound understanding of the underlying mechanisms that drive the use of such innovations may help marketing practitioners to better meet consumer needs and to develop more efficient communication strategies.

1.2 Research Questions

In consequence of the theoretical as well as practical importance of attitude formation in innovative technology markets, this thesis's object of cognition focusses on the consumer acceptance of wearable computing. Thus, the overall aim of this study is to conceptualise and explain key factors that lead to either acceptance or rejection of wearables. Building on this epistemological interest and considering the stated insufficiencies and knowledge gaps in diffusion and Information Systems research, this thesis is guided by the following fundamental research questions:

1) What domain-specific drivers at individual-level determine the acceptance decision towards wearable computing?
2) What issues are most salient adoption inhibitors from a consumer's viewpoint?
3) What personality traits influence technology adoption behaviour?
4) In terms of causality, how can these factors be suitably contextualised and transferred into a cohesive explanatory model of wearable technology acceptance?

Drawing on the theoretical findings which are based upon extensive literature review as well as exploratory study results, the quantitative research phase further investigates the following questions:

5) Based on empirical evidence, to what extent do the identified factors of the integrative framework affect consumer acceptance?
6) What implications for marketing practice and research can be deduced from the empirical findings?

Along with these questions, both the research design and the thesis structure emerge, which are discussed in the next section.

1.3 Structure of the thesis

In respect of the mentioned need for research in the chosen field, the present thesis should provide sufficient evidence to answer the main questions. To achieve this objective and to gain profound insights, this work employs a multi-methodological approach, interlinking conceptual, qualitative and quantitative studies. Hence, the outline of this thesis follows the research strategy as depicted in Figure 1.1. In total, it encompasses eight chapters that are divided in a qualitative and a quantitative part. The qualitative part provides both the theoretical background and conceptual considerations on the research subject. Moreover, it describes the qualitative study design and synthesises the identified relevant acceptance factors to a new, dedicated path model. The initial exploratory thematic block therefore grounds the subsequent quantitative study, which aims at empirically validating the proposed cause-effect model.

In **Chapter 2** the novel wearable computing paradigm is discussed in order to attain a conceptual context and to set a frame of reference for the main research object. A characterisation of wearable computing together with the striking design challenges is given to provide an understanding of the relevant terminologies, potential benefits as well as possible usage risks. In addition, a classification scheme is proposed in order to better differentiate and identify wearable devices. The chapter finishes by outlining the current market situation from an application and device type perspective.

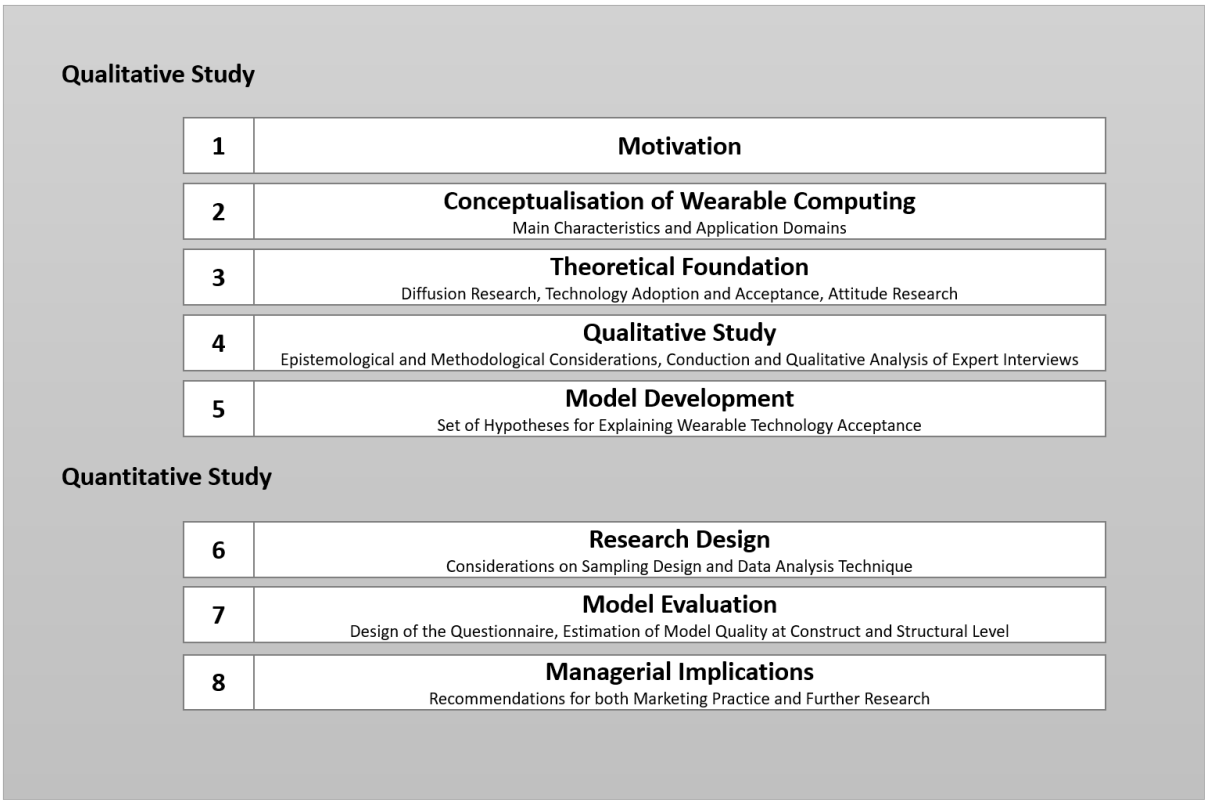

Figure 1.1: Structure of the thesis

Chapter 3 is concerned with theoretical models and principles related to the field of Information Systems as well as innovation adoption. Key foundations and frameworks in these areas are described in detail and also critically evaluated in a technology adoption context. Additionally, important concepts from the thematic area of perceived security are outlined. Overall, the theoretical substantiation of the study is approached by combining different research streams in order to attain a sufficiently holistic system of statements. The underpinning theories and models in technology acceptance and Information Systems research provide the starting point for the qualitative study and subsequent hypothesis formulation.

Chapter 4 is dedicated to the qualitative exploratory study commencing with epistemological and methodological considerations. The application of methods triangulation, which involves a combination of qualitative and quantitative methodologies, is justified. Subsequently, the chosen empirical setting is outlined. The chapter closes by delineating the qualitative data analysis and presenting the inductively generated results. The findings identify the relevant concepts that affect wearable computing adoption.

Chapter 5 deals critically with the conceptualisation of acceptance-enhancing factors impacting the individual intention to use wearable technologies. Based on the results from both the qualitative and the conceptual study, hypotheses are successively derived for the Wearable TAM. The research model links the identified influence factors by placing them in logical correlative interrelationships. Since contemporary research gaps as well as the results of the qualitative study prompt this, particular attention is directed to commensurable theories in the area of IT security and personality psychology. In order to augment the Wearable TAM with further informative variables, interacting effects of relevant moderating variables are also identified and integrated into the nomological net.

In **Chapter 6** information is provided about philosophical approaches and the most appropriate research design. Also, some basic methodological considerations with regard to multivariate data analysis are made and a specific statistical method is chosen and detailed (i.e. structural equation modelling). The chapter is completed by a literature-based operationalisation of measurement instruments for the hypothesised constructs that are used in later analysis.

Chapter 7 elaborates on the chosen research strategy for the empirical study including the decision on the proper sample size and sampling procedure. Careful consideration is also given to the development of a suitable questionnaire design to reduce method bias. Afterwards, descriptive statistics of the survey results are presented together with an assessment of the representativeness and normality of the selected sample data. The chapter proceeds with an empirical purification of the operationalised measurement models to warrant quality of construct measurement. Subsequently, the entire conceptual framework advanced in chapter 5 is evaluated quantitatively by means of variance-based structural equation modelling. In addition, the research model is tested for systematic group differences to determine its robustness. The section closes with a synthesis of the empirical findings in order to establish new scientific insights.

Finally, **Chapter 8** summarises the entire study and outlines the novel contributions of this work to current Information Systems research. Based on the key findings, multiple implications for marketing practitioners are deduced. The thesis concludes with an overview of the major limitations of the study and promising directions for future research.

2 Wearable computing

This chapter introduces the technological context of the present research. It presents a characterisation, definition and classification of wearable computers, along with a brief demarcation from other mobile technologies. Two actual examples are discussed in more detail. Also, major design challenges of wearables are portrayed to create a thorough picture of the subject. Then an overview of the current market situation is given, which shows from different angles the current state of diffusion of these new devices. In sum, this chapter sets the frame of reference for the focal study object.

2.1 Conceptualisation of Wearable Computing

The convergence of various technological innovations in mobile and ubiquitous computing has fostered a promising new transdisciplinary field referred to as wearable computing. This new paradigm has the goal of providing computational services anytime and anywhere in an unobtrusive manner. By bringing together expertise from diverse research fields, ranging from computer science and electrical engineering, through material science to human-computer interaction and, not least, artificial intelligence, the integration of people, environment and technology is becoming more and more foregrounded. Consequently, the universal notion of wearable computing covers a broad spectrum of concepts and implementations: In the broadest sense, the terms 'wearable technology' or 'wearables' both relate to computer systems or electronic technologies that are body-worn and utilised mostly hands-free (Bass, et al., 1997, pp. 34-39; Tehrani & Michael, 2014). Due to the remaining diversity in possible functional and technical implementations arising from this ambiguous definition, wearable devices are generally particularised and differentiated from other computer types by means of several concretising properties (Herzog & Witt, 2009, p. 10). A first narrower conceptualisation is provided in (Rhodes, 1997, pp. 218-224). Here, wearable computers are attributed by five characteristics:

- Portable while operational
- Enabling hands-free or one-handed utilisation
- Providing sensory features, e.g. Global Positioning System receivers, accelerometers or cameras
- Proactive notifications, attracting the user's attention
- Constantly running and accessible

Specifically, the aspect of portability makes up the central differentiator between wearable and ubiquitous computing (Rhodes, et al., 1999, pp. 141-149), since wearable computers are conventionally defined as "fully functional, self-powered, self-contained computers" (Barfield & Baird, 1998, p. 157). In contrast, ubiquitous computing necessitates distributed computing environments (Bauer, et al., 2002, p. 785), pervading our surrounding world with small-scale, networked ICT components cumulatively.

Both the ability of sensing and attracting the user's attention implicate certain interface capabilities as well as the presence of a local storage, allowing for data capture and – in view of e.g. wireless sensors or other on-body communication networks – a minimum level of communication-capability and connectivity. In comparison to mobile computing, especially the wearable's **non-obtrusiveness** character is accentuated in the academic

literature. Mann (1998) clarifies this by introducing the "personal empowerment" requirement, focusing on a synergetic symbiosis between man and machine. Within this new paradigm computing is seen as a peripheral task, assisting the user's primary activities seamlessly and unobtrusively to the greatest possible extent. Moreover, given that wearables ought to be non-distracting, easily accessible everyday companions, **multimodality** (in terms of the variety of human-computer interaction modes, e.g. speech, gesture or biometric iris recognition for data input) has repeatedly been mentioned as another critical capability (Munteanu, et al., 2016). After all, the devices' typical small form factors place intrinsically high demands on the design of Input/Output modalities (e.g. gesture-based data entry). Considering the dynamic environment changes in wearable computing settings, interaction modalities should also be able to adapt to the given circumstances (Starner, 2001a, p. 46). Meanwhile, even thought control of wearables is assumed to be an inevitable evolutionary step in next-generation technologies, as this kind of interaction provides the most natural and intuitive way of manipulating information (Powell, et al., 2013, pp. 427-435).

Complementarily, Kortuem et al. (1998, p. 61) postulate the 'augmented-reality' criterion, which means that wearable computers should be capable of "focusing the user's attention and presenting information in an unobtrusive, context-dependent manner". Hence, in comparison to the aforementioned five characteristics of wearable devices the attribute **context-awareness** is particularly emphasised. Basically, context-awareness describes the ability of a system to sense, interpret and respond to certain environmental states. Thereby, the term 'context' can be related to any interaction-relevant entity, such as a person, place or object (Abowd, et al., 1999, pp. 304-307). Thus, context recognition scenarios should generally incorporate the wearer's physiological state, his current tasks and environment's characteristics (e.g. location, time or available infrastructural components) as well as the wearable's internal state (Bristow, et al., 2004, pp. 798-800). Pascoe enumerates in (Pascoe, 1998, pp. 92 - 99) four core context-aware application categories, including:

- *Contextual sensing*
  Detection and presentation of contextual information on the user's behalf as a main feature.
- *Contextual adapting*
  Behaviour depends on the prevailing circumstances.
- *Contextual resource discovery*
  Recognition and exploitation of network-compatible, interoperable ICT systems in terms of machine-to-machine interaction.
- *Contextual augmentation*
  Annotating with descriptive metadata segments of reality that are of particular interest.

Context sensing enabled by enhanced multisensory capabilities is increasingly considered to be a constituting property. For instance, Tehrani et al. stresses in (Tehrani & Michael, 2014) that advanced scanning and sensing technologies still shape the distinct character of wearable computers compared to contemporary hand-held devices, such as tablet PCs and laptops. Rather than responding to changing environmental states solely by explicit communication, wearable computer devices should additionally observe and react to manifold contextual cues automatically. As a consequence, context modelling is regarded as a basic supplementary criterion for sensory augmented computing (Bharatula, et al., 2008, p. 123). Considering that smart wearable systems are individual's daily life supporting, omnipresent socio-technical tools, they should be able to model the situational context as

well as the wearer's preferences, abilities and prevailing needs in order to proactively provide adequate information and behaviour. Ultimately, they should superimpose the reality with an associated information structure, augmenting the human perception and thus enhancing the user's efficiency (Barfield, 2015).

Taken together, the idea of wireless on-body communication bridges the gap between **ubiquitous computing** (also being referred to as Internet of Things) and wearable technologies. The latter provide connectivity to the fixed ubiquitous computing infrastructure in real-time and, therefore, can be rather described as an integral part of ubiquitous computing. While the ubiquitous computing paradigm builds upon the pervasive presence of networked objects such as radio-frequency identification (RFID) tags, actuators, mobile phones and sensors, wearables can be used to connect humans to these networks (Hao & Helo, 2017). In other words, ubiquitous computing is distributed to the surroundings, whereas wearable computing is performed by the user. Notably, the term 'things' in a ubiquitous computing sense refers to objects equipped with microchips, sensors and wireless communications capabilities, e.g. connected cars, smart home appliances, drones, etc.

Furthermore, since wearables respond to the trend towards the Internet of Things (IoT), their primary communication is rather with other interconnected devices than with the user (Marzec, 2014). Consequently, the wearable computer research community often refers to the modular ecosystem of wearable electronics, built on innovative types of sensors and other radio nodes, e.g. smartphones and smart home appliances (Gartner, Inc., 2013b). As a result, electronics companies might increase customer retention by implementing a corresponding product portfolio strategy that creates switching barriers. In an IoT sense, especially interoperability across devices is thought to become a key differentiating factor that will contribute to the generation of brand loyalty (Marzec, 2014). In addition, beside the above stressed criteria of mobility and augmented reality, the author points out the convergence of **big data** and smart wearable artefacts. Ultimately, employment of big data analytics in wearables (considering e.g. health analytics companies) permits vendors to capitalise on non-transactional data and, thus, to gain and sustain competitive advantage (Weathington, 2014).

Taking into account all above conceptual considerations, it is not surprising that scholarly literature does not yet provide a profound definition of wearable computing. As Steve Mann put it, "[…] the definition of wearable computing can be kind of fuzzy itself. Thousands of years ago, in China, people would wear an abacus around their neck — that, in one sense, was a wearable computer" (Bilton, 2012). The concepts of wearables vary by both researchers and practitioners and are apt to be adjusted as technology evolves. Nevertheless, to arrive at an operational working definition, the key attributes of wearables made above may be condensed as follows:

> *Wearable technologies are constantly running, body-worn devices that provide computational power as well as automated feedback and collect personal data through a range of sensors, so that information processing and, where appropriate, communication is possible anywhere and anytime in an unobtrusive and context-aware manner.*

As opposed to classic handheld devices such as mobile phones, wearable technologies target at device miniaturisation in order to operate as unobtrusively as possible. They work without any interruption and are even stronger intertwined with the human body. Being the most pervasive implementation of IoT to date (European Commission, 2016, p. 18), wearable devices have a great potential to fulfil the vision of ubiquitous computing. They are considered the most personal devices in the evolution of communication and information technologies

and, as such, carry huge potential to dramatically change the way people communicate and companies interact with consumers (Ericsson Consumerlab, 2016; Rauschnabel & Ro, 2016, p. 124).

2.2 Towards a Classification Scheme

Although the first wearable computer as a cigarette pack-sized roulette prediction system was already pioneered at Massachusetts Institute of Technology in 1960 (Edward O. Thorp‘s self-reported first wearable computer consisted of a twelve-transistor CPU and was hidden in shoes, see Thorp 1998), the research field of wearable technology is fairly new. In fact, the evolution of wearables has been spurred by the military sector almost 50 years ago, where highly portable computer devices with constant and non-distracting access to information services, such as head-mounted displays, feature great usefulness (Rizzo, 2013; Rhodes, 2001). Accordingly, wearable technologies were initially employed in vertical niches, particularly in military and industrial spheres (Billinghurst, et al., 1999 p. 58). The focus of those special purpose wearables was mainly on hands-free and instantaneous interaction with information. Nonetheless, over the past decade there has been a shift in the primary scope and understanding of the concept of wearable computing towards the ultimate goals ‘proactiveness’, ‘responsiveness’ and ‘context-awareness’ (Viseu, 2003 pp. 77-79). As a result, wearable computers migrated from simple information processing equipment to ‘extensions of the self’ or a ‘second skin’, augmenting the physical world through digital mediation.

The advent of wearable computing as a generally acknowledged study area can be traced back to the late 1990s when the first IEEE international symposium on wearables was hosted in Cambridge (Cook & Song, 2009, p. 83). Since then, the application domains as well as product diversity have expanded significantly, so that wearable devices are expected to carry a disruptive influence on the technology market in the near future (PR Newswire, 2014). At present, there are several approaches to segment smart wearable devices. First of all, one can differentiate between ‘wearable computers’ and ‘wearable technology’. The latter generic term subsumes not only the former one, but by definition also the functional clothing platform in its broadest sense. Therefrom, the notion of wearable technology does not necessarily include algorithmic processing (Hännikäinen, 2006, pp. 6-7). However, as this concept is generally associated with some form of electronic functionality (e.g. transistors and independent processing capabilities) by both the research community and the general public, in the following the term is understood as involving some form of computational capability. Consequently, the concepts wearable computer and wearable technology are used interchangeably throughout this thesis.

Up until now, though, there is no global system of classification available to understand the scope of impact wearable devices have across different consumer markets. From a consumer point of view, Lajos (2010) emphasises that categorisation of consumer goods is “[…] a fundamental cognitive phenomenon in the consumption process because it enables consumers to differentiate between products.” In order to establish a classification scheme that allows to properly systematise the landscape of wearable computing products, this thesis follows the principles for taxonomy construction set out in (Alrige & Chatterjee, 2015, pp. 496-504). The authors developed and tested a taxonomy for wearables in healthcare. They propose to first define the term for which the taxonomy will be constructed. This has already been accomplished in section 2.1. Subsequently, based on the definition laid down, the major dimensions of the taxonomy that characterise the focal concept should be specified.

As shown, wearable computing is marked by both digital assistance of certain tasks (i.e. they serve a purpose) and a garment or 'wearability' characteristic for effectively utilising human body areas. In line with this attribution, in-depth literature search shows that **field of use**, **functionality** and **form factor** are common themes in commercially available ICT products that correspond to the present working definition of wearable computers (see chapter 2.1 on the characterisation of wearables which underlines the *ubiquitous* provision of assistive information services, the *context-awareness* arising from single-sensor and multi-sensor functionality, as well as the *unobtrusiveness* of such ultra-mobile devices). Hence, this research adopts a taxonomy for wearable technologies that revolves around these three dimensions.

In terms of form factor, Kumari et al. (2016, p. 302) advocate to employ two broad groups of usage, namely 'electronic devices' and 'apparels and textiles'. Generally, the former category refers to **accessory** type devices that can easily be attached to the body including wristwear such as smartwatches and activity-tracking wristbands, smart jewellery (e.g. rings and necklaces), belts, earbuds and eyeglasses. On the contrary, the latter category refers to textile-integrated electronics (also known as 'smart textiles' or 'e-textiles'), which can interact with the user or environment and are potentially capable of accomplishing a wide spectrum of functions, as well. Such **garment-based** wearable systems are intended to be worn throughout the day like an article of clothing. Examples would include smart shirts and jackets, Bluetooth gloves, intelligent shoes, smart socks or underwear. Unlike accessory type devices, smart garments are usually designed as special-purpose wearable computers (Hännikäinen, 2006, p. 7). Even though skin patchable devices and implants such as digital lenses and smart tattoos are deemed to play an increasingly significant role in the future (Ray, et al., 2016, p. 124), this thesis does not include such wearable appliances, since their installation naturally involves a quite invasive procedure. This would clearly run counter the established understanding of wearables as being easily applicable day-to-day products for mass markets.

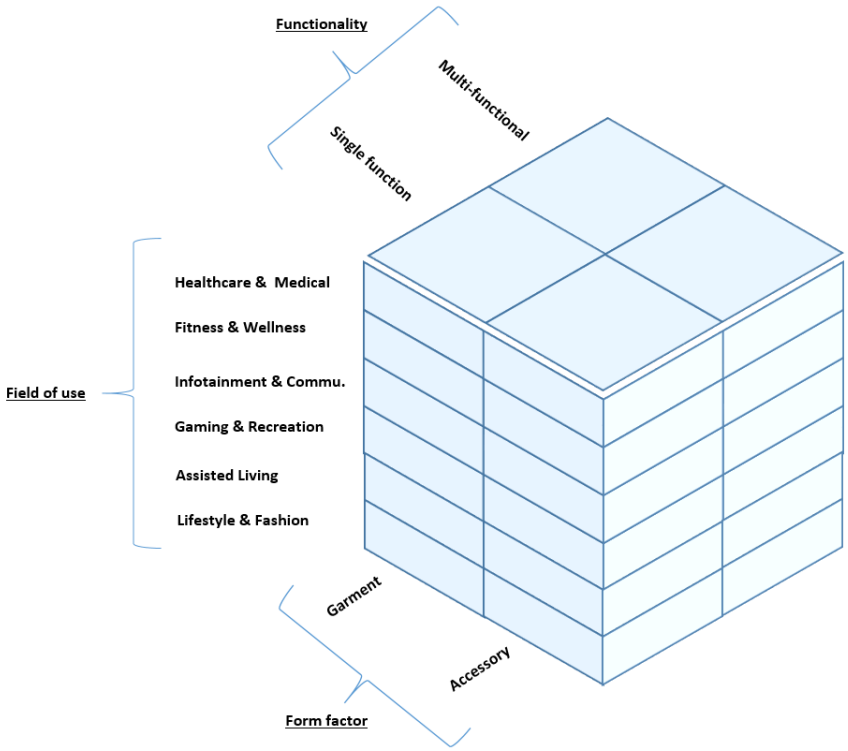

Figure 2.1: Taxonomy of wearable computing (Based on Alrige et al., 2015, pp. 496-504)

Furthermore, wearable technologies can be categorised as **single function** (special purpose) or **multi-functional** (multi-purpose) (Bruno, 2015, p. 13). For instance, activity trackers are usually designed to monitor specific fitness-related metrics, whereas many smartwatches can serve a number of different functions at the same time such as pulse measurement and navigation. In most cases, single function wearables can be directly allocated to a distinct field of use (e.g. activity trackers support physical fitness), whereas multi-functional devices represent often hybrid products that serve more than one application. With regard to the field of use, a widely adopted categorisation is provided in a whitepaper by IHS Electronics and Media (IHS, 2013), a business intelligence organisation which offers market data and forecasts in the electronics, medial, transportation, and energy industries. The report assesses five applications, including **healthcare and medical**, **fitness and wellness**, **infotainment**, industrial and military. Since the present research centres on the consumer market, the latter two categories had to be discarded. In addition, a thorough literature review revealed that **gaming and recreation**, **assisted living**, as well as **lifestyle and fashion** reflect further important purposes that should be considered in a wearable computing context (cf. Hunn, 2015, p. 8; Park, et al., 2014, p. 8; Bothun, et al., 2014, p. 19; Tehrani & Michael, 2014). All in all, the six relevant fields of use identified can be characterised as follows:

- **Healthcare and medical**: Used to monitor a diagnosed condition and to support diagnosis where possible, e.g. diabetes care, blood pressure and ECG monitors, etc. Typical products include glucose and blood pressure monitors (e.g. continuous glucose monitoring technologies such as 'Google Contact Lens' which is capable of measuring blood sugar levels in tear fluid through integration of miniaturized glucose sensors, wireless circuits and displays, see Park et al., 2018), biofeedback patches, hearing aids and wireless EEG headsets.
- **Fitness and wellbeing**: Used to monitor bodily vital signs, e.g. nutrition, activity, emotional measurement, etc. Typical products include activity-tracking wristbands, smartwatches and smart sportswear such as heated jackets, GPS ski mask or smart training shoes.
- **Infotainment and communication**: Used to inform and entertain, e.g. emails, directions, notifications, shopping insights, etc. Typical products include Bluetooth headsets, head-up displays, smart glasses and smartwatches. This field of use may also contain tourism and education applications, e.g. library applications or medical education. Again, typical products include smart glasses and smartwatches.
- **Gaming and recreation**: Used to make gaming more visually and physically engaging, e.g. through virtual reality and interactive gaming. Typical products include virtual reality headsets and augmented reality smart glasses.
- **Assisted living**: Used to increase productivity and simplify daily tasks, e.g. home automation, mobile payment, automotive monitoring and controlling, remote identification, etc. Typical products include smartwatches and smart glasses. This field of use may also subsume applications for safety that are used for personal security (e.g. 'wearable panic button') and monitoring pet's and other people's activity (e.g. babies, elderly). Typical products include smartwatches and wristbands, smart jewellery and key chains.
- **Lifestyle and fashion**: Used for lifestyle and fashion statements, e.g. light embellishment, decorative display, etc. Typical products include fashionable jewellery and smartwatches.

Taking the above established subdimensions of the final structure of the taxonomy together, a 6*2*2 cuboid emerges, which is illustrated in Figure 2.1.

Table 2.1 gives an example of the application of the taxonomy on several commercially available products.

Product	**Primary Field of Use**	**Form Factor**	**Functionality**
Microsoft HoloLens (Microsoft, 2017)	Infotainment and communication (including tourism and education), gaming and recreation	Accessory (mixed-reality smartglasses)	Multi-functional
HTC Vive (HTC Corporation, 2017)	Gaming and recreation	Accessory (virtual-reality smartglasses)	Single function
Pebble Smartwatch (getpebble.com, 2017)	Fitness and wellbeing, infotainment and communication	Accessory (smartwatch)	Multi-functional
Altra IQ Smart Shoe (Altra, 2017)	Fitness and wellbeing	Garment (smart shoe)	Single function
Jawbone UP Move (jawbone.com, 2017)	Fitness and wellbeing	Accessory (wristband)	Single function

Table 2.1: Exemplary application of the taxonomy

As wearable computing is a relatively new and evolving field, this taxonomy can be extended in order to take new cases into account. In light of the present study subject (acceptance of wearable technologies in general consumer markets), it appears appropriate to concentrate on accessory-based, multi-functional wearable systems. They allow to target a broader scope of application and thus a broader user audience as compared to special purpose wearables such as insulin pumps or ring wearables that match outfits. More specifically, smartwatches and smart glasses seem promising for scholarly examination, since these technologies naturally span multiple cells of the classification scheme as regards their field of use. This renders them particularly auspicious for the mainstream market. The next subchapters provide therefore a detailed characterisation for smartwatches and smart glasses.

2.2.1 Smartwatches

As with any other wearable device, academic literature lacks a precise definition of the smartwatch technology. Various wrist-worn devices as diverse as fitness trackers and intelligent bracelets are often summarised under the same concept (Chuah, et al., 2016, p. 277). Basically, smartwatches are mini computers that are worn like a traditional watch. They gather personal data through multiple sensors, provide wireless connectivity and alert notifications (Wu, et al., 2016). Additionally, Chuah et al. (2016, p. 277) maintain that, in contrast to other wristwear tracking a user's physical functions, smartwatches provide relatively large displays (often touchscreens) and their operating and app eco-system allows to install and use numerous apps. For instance, there are currently more than 4,000 apps available for Android Wear, more than 6,000 apps for Pebble and more than 10,000 apps for iOS (Apple) (Curry, 2015; Chuah, et al., 2016, p. 277). This clearly broadens their scope of application as opposed to smart wristbands. Moreover, rather than just collecting vital parameters, smartwatches are usually designed to provide relevant information such as emails or status notifications from social networks. These

wearable gadgets are thus most beneficial when they are connected to the Internet (Wifi, mobile Internet or Bluetooth).

Because most smartwatches are supposed to seamlessly integrate with existing technologies in general (e.g. tablet computers or smart TVs) and smartphones in particular, they can naturally be divided into two spheres of wearables: as standalone devices that act as centralizing hubs for communication and information, and secondary wearables, which serve as interfaces to smartphones that automatically synchronise their data in real-time (Bothun, et al., 2014, p. 6). It is therefore not surprising that the magnitude of ICT vendors tries to create new demand for their mobile devices by increasingly investing in wearable computing research and development (R&D) activities (Jung, et al., 2016, p. 899). It is particularly since Apple launched its Apple Watch in early 2015, that the global market for wearable devices gained its initial momentum. Especially enthusiastic Apple consumers were interested in in the new product that the company has introduced to the market. They transferred more positive attributes to the Apple Watch due to extant strong emotional connections with the brand (Rauschnabel & Ro, 2016, p. 130; Richter, 2016). Driven by such *spillover effects* from one type of mobile device to another, the smartwatch market has experienced a significant growth in 2015. Since then, various other companies including Samsung, Motorola and LG have produced their own lines of smartwatches. Some market analysts even expect smartwatches to pave the way for mainstreaming the entire wearable computing category (Jung, et al., 2016, p. 899).

Currently, smartwatches are mostly peripheral devices, indirectly connected to wireless networks via smartphones. However, according to some researchers, untethered devices that can transmit and receive data without the need for a connectivity hub (i.e. mobile phone) will considerably drive future market for wearable technology forward (IDC, 2016). Correspondingly, a recent conjoint analysis suggests that consumers primarily value the functional aspects of wrist computers and that potential users regard smartwatches as being independent digital devices rather than accessories for smartphones (Jung, et al., 2016, p. 904). If smartwatches were more autonomous and capable of standalone communication, they could serve diverse functions and ultimately even replace smartphones in some respects (Elgan, 2016). Thus, standalone capability is of great significance to the positioning of smartwatches. It may be concluded that this attribute is also key for other wearable device types such as smart glasses.

2.2.2 Smart glasses

Smart glasses mark the latest phase in the evolution of Internet technologies. They take the idea of the second and third-generation Web even a step further: While both generations – commonly referred to as ‘Web 2.0’ and ‘Web 3.0’, respectively – emphasise interactive and semantic Internet technologies, smart glasses aim at melding the real and the virtual world in the consumer’s view field (Rauschnabel, et al., 2015a). In this category of wearables, Google Glass (‘Project Aura’) was the first commercially launched product for personal use. Smart glasses are worn like regular eyeglasses but feature a prism positioned in front of the wearer’s right eye to display virtual content. They capture data from the physical world through several sensors including camera, microphone as well as GPS receiver, and they normally provide mobile Internet technologies (Quint & Loch, 2015, p. 205). Depending on the model, users can seamlessly interact with the glasses by means of natural language voice commands, built-in touchpad, head motion, or virtual displays (e.g., holographic buttons). Figure 2.2 exhibits the typical functionality of augmented reality data glasses.

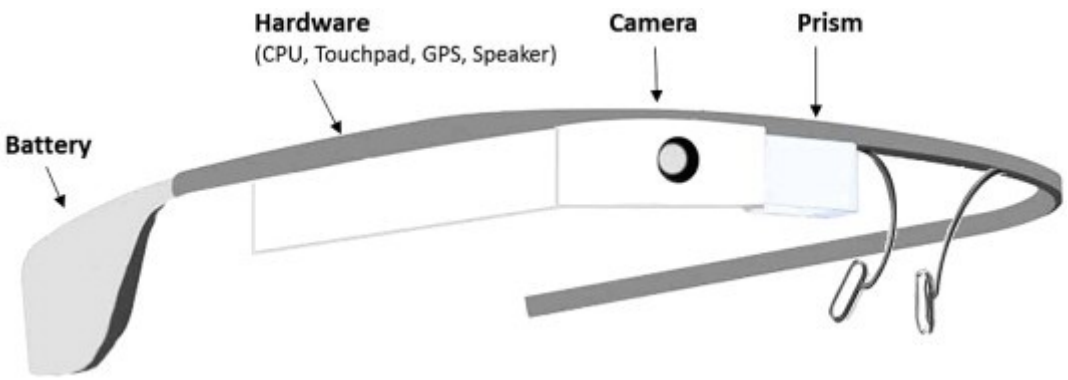

Figure 2.2: Design features of Google Glass (Rauschnabel, et al., 2015, p. 636)

Principally, a distinction can be made between virtual reality and augmented reality glasses (Rauschnabel, et al., 2015b, p. 7; Goldman & Falcone, 2016). Virtual reality devices are entirely closed-off from the real world, completely immersing the user in an artificial, computer-simulated environment or real-life remote location. Due to this characteristic, they particularly offer tremendous opportunity for pervasive gaming experiences (Tung, et al., 2015, p. 3327). Thus, major commercial applications to date include gaming and recreation (e.g. video, sports, etc.). Strictly speaking, virtual reality devices form therefore a product category of their own as implied by the developed taxonomy in section 2.2. These technologies are typically supplied in the form of head-mounted displays such as Oculus Rift, Sony PlayStation VR or HTC Vive. In contrast, augmented reality glasses (sometimes also referred to as 'mixed-reality') such as Epson Moverio or Microsoft HoloLens overlay digital information onto the real world, resulting in a composite, augmented reality view. Consequently, they correspond more closely to the above definition of smart glasses and are thus used synonymously in this thesis.

Since smart glasses allow the user to look straight out at the world free-handed, they provide a radically new interaction situation along with various novel application opportunities (Due, 2014, p. 2). Previous research has explored the utility of augmented reality glasses in a number of different contexts. For example, Mitrasinovic et al. (2015, pp. 381–401) have studied new and potentially disruptive clinical and surgical applications of smart glasses. Quint and Loch (2015, pp. 203-208) have explored the use of augmented reality technologies in maintenance processes as a means of safely producing video records. Hein and Rauschnabel explore in (2016, pp. 83-109) the opportunities of data glasses in enterprise social networks. In the consumer sector, Due (2014, pp. 1-21) discusses health applications of smart glasses for people who suffer from cognitive disorders (e.g. Alzheimer's), task-related applications for Do-it-yourself enthusiast (e.g. instruction manuals, virtual furnishing planners and cooking guides), and lifestyle applications for so-called *quantified selfers*, who wish to measure and document their behaviour, body signals and environmental exposure.

In sum, augmented reality smart glasses promise a vast range of possible use cases, some of which are not recognised yet. However, as with any new and potentially disruptive technology that challenges existing social norms, market success of smart glasses might be limited due to various technological and socio-psychological factors (Rauschnabel, et al., 2016 p. 7). The next chapter is thus devoted to the barriers of a widespread wearable technology usage.

2.3 Challenges to Adoption

Given the above characteristics of wearable computers, several derivable constraints on architecture design become acute. In respect of the multitude of severe design issues, Siewiorek et al. (2008, p. 2) suggest to systematise architectural challenges among three interacting axes for problem structuring. The first axis is referred to as the **human axis**, which deals with the problem area of 'wearability'. This concept primarily addresses the ergonomics of the devices' physical shape (Dunne & Smyth, 2007, pp. 299-302). Aside from traditional system performance measures, the degree of physical, mental and emotional comfort is of particular relevance, as user convenience is essential to effectively afford superior benefits for body-mounted computers. Accordingly, critical design topics are e.g. form, weight, heat generation and aesthetic properties (Bharatula, et al., 2008, p. 124). Closely related, the **computer axis** is concerned with hardware construction-related problems. Among other properties, for example heat dissipation, size, power consumption and interface capabilities have to be considered here. Finally, the **application axis** addresses the design of mobile application software with the objective of developing most suitable software solutions for different purposes.

Yet, in technical terms there is a trade-off namely between the wearability and suitability criteria, in particular with regard to the increasing importance of computation power and energy consumption. Whilst miniaturisation proceeds to the benefit of user comfort, real-time applications grow increasingly sophisticated (e.g. by making extensive use of sensors or by natural language and image processing) and therefore also computation- and energy-intensive (Fernando, et al., 2013, p. 84). Moreover, due to the wearable's reduced battery size which mainly dominates its form factor (Lotfian & Jafari, 2013, p. 913), networking becomes more restricted compared to stationary computers. In sum, their resource scarceness together with their limited computational capacities and local storage facilities frequently force a thin-client approach, where services are provided by fixed-infrastructure servers (Starner, 2001b, pp. 54-57). From an IoT perspective, some market analysts consider the ability of wearables to account for and to interact with environmental surroundings even a critical inflection point of the entire product category (Bothun, et al., 2014, p. 4; Ericsson Consumerlab, 2016).

Nonetheless, driven by fast progress in mobile wireless communication and hardware architecture, the stated design constraints become more and more a non-issue. For instance, emerged mobile cloud computing technologies enable a more efficient exploitation of external computing resources, such as storages, networks and services (Cui, et al., 2013, p. 148). In addition, by way of example, innovative sensing technologies (Zhang, et al., 2013, pp. 300-309), new wireless technology standards for data exchange, e.g. the Bluetooth v4.0 specification, and current display solutions, such as the 'electronic ink' (E Ink Holdings Inc., 2012), promise a noticeable reduction in energy consumption. On the contrary, IT security threats still remain a significant challenge for system designers (Thierer, 2015, p. 5). What is more, in light of numerous unprecedented applications and services, dynamic interconnections and a variety of sensors, several further multilateral information security and privacy concerns arise (Migicovsky, et al., 2014, p. 1). Especially the continuous use of wearable technologies which continually collect, process, and transmit personal data might lead to severe privacy implications and threats such as data misuse by third parties or public surveillance (Motti, et al., 2015 p. 232).

In respect of the distinguished capabilities of wearable devices, the research agenda of wearable computing ascribes security issues a very high priority (Hausman, 2013; Thierer, 2015, p. 4; Rawassizadeh, et al., 2015, p.

47). The new vulnerabilities primarily introduced by the ubiquitous computing paradigm pose an imperative need for novel prevention, avoidance and detection technologies beside those for traditional distributed systems (Yamada & Kamioka, 2005, p. 846). In this context, ubiquitous computing-related security risks can be directly transferred to the field of wearables, as smart garments can be deemed special applications of IoT (Want, et al., 2015). In particular, the transient interconnections in heterogeneous ICT landscapes, where spontaneously invoked interactions are mostly ad-hoc in nature, entail partially *incompatible security schemes* regarding the inter-operating network nodes (Venkataram, 2010). Over and above the long-established security issues in wireless environments (considering for example the greater susceptibility to eavesdropping and other malicious attacks due to more contact points) these different levels of security may additionally give rise to unauthorised or unnoticed manipulation of data (Lyytinen, et al., 2004, pp. 701-702). Overall, the absence of a centrally controlled network imposes advanced information security mechanisms concerning data privacy and information integrity. However, again the limited computational resources of wearables constrain available security mechanisms such as encryption algorithms and integrity checks, as they place some demand on CPU power (Lindström, 2007, p. 4). In addition, against the backdrop that small devices are generally equipped with very scarce resources like computing power and energy, the propagation of denial of service attacks is significantly facilitated (Ochrymowicz, 2011). Again, this marks a goal conflict between usability and security issues. Furthermore, apart from a possible non-cooperation of nodes, compromising the availability of task-critical services just as is the case with the finite battery power, a sufficiently complex, dynamic topology in conjunction with a plethora of novel services could cause unexpected feature interactions as well as unplanned growth and unpredictable ensuing flaws (Stajano, 2010, p. 282; Lyytinen, et al., 2004, p. 702). Needless to say, that achieving critical mass of adopters makes attacks more profitable.

Yet, the above stated security threats, largely arising from arbitrary data exchange in partly unsecure networks, are by far not all. One of the major concerns in the context of wearable computing environments is that of *context information privacy* (Wrona & Gomez, 2005, p. 261; Robinson, et al., 2005, p. 5; Almutairi, et al., 2012, pp. 195-198). As context-aware applications continuously capture and interpret the user's physiological and environmental state by several sensors, the wearable becomes a social surveillance system that incorporates a great deal of privacy-sensitive information. Correspondingly, a recent survey found that privacy is one of the key apprehensions of consumers (Li, et al., 2016, p. 8). According to the survey data, 82% of respondents were concerned that wearable devices could invade their privacy. By means of a qualitative content analysis, Motti and Caine (2015, p. 242) explored what privacy concerns users have. They identified different aspects of user interaction with a wearable device including disclosure of sensitive information, subtle data collection (audio and video), public posts in social media apps (sharing), and lack of control and awareness regarding who has access to the data collected. Hence, protection from unauthorized data access and data abuse (i.e. the inappropriate use of data in which private information is released to untrusted environments) seems crucial for a high adoption rate and widespread diffusion of such systems.

Albeit privacy exhibits such a paramount of importance, information security is in general a holistic quality due to its manifold nature, systemically inherent in ICT systems by addressing all layers of the protocol stack. According to Stajano's understanding of the term 'security', this concept basically refers to risk management, focussing on worthwhile defences of assets (e.g. computer platforms or pieces of information) against threats,

arising from intrinsic system weaknesses (Stajano, 2010, p. 4). This understanding conforms to U.S. law which defines information security as "[...] protecting information and information systems from unauthorized access, use, disclosure, disruption, modification, or destruction [...]" (44 U.S. Code § 3542, 2002; see also chapter 3.2.2 on the ISO 27000 international standard). Traditionally, the concept of security subsumes the following fundamental triad of attributes, referred to as the CIA security goals:

- **Confidentiality** (Privacy): This security core principle is violated if privacy-sensitive or proprietary information is accessed or disclosed by unauthorised entities – whether by human beings or machines. Closely related to this criterion is the privacy aspect. In comparison, the latter security principle applies to people, whereas the former applies to data. Thus, the concept of confidentiality represents semantically an extending component of privacy (Andress, 2011, p. 4). As the present work seeks to gain insights into the technology adoption process from a consumer perspective and given that the terms 'privacy' and 'confidentiality' are often used interchangeably in literature (Prewitt, 2011, p. 41), in the following course of this thesis both concepts are treated synonymously.
- **Integrity**: The notion of integrity refers to the ability to safeguard information against unauthorised modification or destruction, whereby data could be altered either within a host or during network transmission.
- **Availability**: This final key concept is contravened whenever authorised principals cannot access task-relevant information or services in a timely manner. High availability systems guarantee preservation of reliability and availableness to the greatest possible extent by preventing service interruptions due to e.g. power loss, application failures or network attacks.

Although these properties shape the cross-domain essence of information security, in a ubiquitous computing environment there are further aspects to evaluate more specifically (Lyytinen, et al., 2004, p. 701; Ochrymowicz, 2011). For instance, as can be derived from the above stated 'authorised' predicate upon which the CIA properties are based, mature **authentication and authorisation** mechanisms are fundamental in a pervasive computing world. Wearable computers require enhanced electronic authentication solutions beyond traditional secret-knowledge techniques due to both their small form factor and their extensive use of personally sensitive information (Lindström, 2007, p. 4). After all, user authentication on such light-weight minidevices via password entry is relatively time-consuming and difficult considering the strained finger placement and the resulting latencies between successive keystrokes. Obviously, this procedure represents an interruption of the wearable usage. Accordingly, a survey assessing mobile device security and usage in 2010 revealed that only 13% of mobile phones are secured with Personal Identification Numbers (PINs) or screen-lock patterns for re-verification (Breitinger & Nickel, 2010, pp. 139-144). This generally implies a high demand for fast and convenient access. Besides, this prevalent method for access control exhibits well-known drawbacks, which oftentimes originate from inappropriate selection and use of passwords (Teh, et al., 2013, p. 1). Therefore, under wearable computing scenarios biometric verification as a mean of confident and user-friendly authentication is at present the most promising procedure for verifying a user's legitimate right. For example, Witte et al. (2013, pp. 29-32) propose a context-aware mobile biometric system, where retrievable behavioural characteristics unique to the user, e.g. speech patterns, are interfaced by corresponding sensors and interpreted as contextual data. This would ultimately meet the trend towards multi-factor authentication, which can be partially attributed to the rise of biometric security

services (Bonderud, 2014). Furthermore, taking into consideration that smart wearable systems might also serve as security tokens in terms of 'master keys' to ease access to multiple other network nodes (especially disconnected hardware tokens which have no physical connection to the computer in combination with a password are a recommended type of security token used in two-factor authentication, see Biryukov, 2015), it becomes clear that a secure online identification is crucial for appropriate data protection (Sun, et al., 2008, p. 1784).

From an end-user's perspective, the authentication property is perceived as both a discrete and substantial dimension of information security (Linck, et al., 2007, pp. 6-8). Following this line of reasoning, the concept of *subjective security* becomes apparent. This construct refers to the individual's perceived information security in terms of a subjectively anticipated probability of illegitimate disclosure, manipulation or destruction of personal data (Chellappa & Pavlou, 2002, pp. 359-360). Yet, even though information security is a multifaceted concept widely accepted, almost all studies on consumer behaviour conceptualise security as a unidimensional construct (Hartono, et al., 2014, p. 11). The assessment of the unique influences which the underlying security dimensions have on attitude formation, however, could provide valuable insights regarding consumer's acceptance decision towards innovative technologies. Hence, the nature of security perception should be specified with respect to its dimensionality and against the backdrop of the investigation scope.

2.4 Market Situation

Due to the sheer number of potential application contexts, the wearable technology landscape is already populated with various vendors across many sectors (Hanuska, et al., 2016, p. 13). Beside most major electronics and fashion companies including Adidas, Google, Intel, Levi's, IBM and Samsung, an eclectic collection of new start-ups emerged that cover a plethora of innovative products and applications, with health and fitness being a key category (Salah, et al., 2014, p. 6). The discussed differences of wearables compared to preceding mobile technology innovations offer various opportunities for existing and new businesses to create value, be it in regard to new business models (e.g. new apps, advertisements, sales generations, etc.), or in terms of internal corporate value creation, for example through improved collaboration and more process effectiveness (Hein & Rauschnabel, 2016, p. 87). Based on the value chain concept that interrelates value-adding activities a firm performs, wearable technologies may provide a source of revenue opportunity for multiple eco-system stakeholders at each link. Effective cooperation models between the involved value chain actors (including device makers, network operators, content and application providers, textile producers, clinicians, insurers, big data storage and data analytics platform providers) can foster creation of business value and market acceptance (European Commission, 2016, p. 16). Within the emerging landscape, many globally established companies have now incorporated wearable electronics into their portfolio to increase the value of their offerings. For instance, as a result of a year-long effort between the Levi's Innovation team and Google's Advanced Technology and Projects (ATAP) group, Levi's pioneered weaving conductive fibres and technology into a denim jacket that allows users to take phone calls, get directions and check the time, by tapping and swiping their sleeves (Samaniego, 2016). Such innovations focus on the existing audience of consumers by combining traditional functions with connected features. Other early-stage entrepreneurial firms have entered the market, which build their business models solely around

wearable computing trends. Prominent examples include Jawbone and Fitbit, both offering exclusively fitness tracking wristbands.

Despite its tremendous opportunities, the evolving wearable computing market is currently still a niche, characterised by a high level of turbulence and uncertainty (Sun, 2016). It can be broadly classified according to geographical and end-use sectors, where key areas include the non-consumer segments medical, enterprise and industrial, military and public safety, but not least also consumer applications such as fitness and sports, fashion and apparel, gaming and entertainment (McCann & Bryson, 2009, pp. 39-41; Mobiquity, 2016; Salah, et al., 2014, p. 8). The healthcare and medical segment consists of products such as sleep monitors and drug delivery, whilst the industrial and military sector comprises products like hand-worn terminals, exo-skeletons and head-up displays. In the manufacturing sectors, foremost smart glasses are expected to increase efficiency and productivity, e.g. through optimising inventory management and quality control (Cross, 2015). When it comes to public safety, for instance augmented reality headsets promise great potential, in that they automatically transmit urgent information encrypted and in real-time (Nguyen, 2015). On the other hand, there is a host of new potential applications of wearables in the business-to-consumer space as well, considering e.g. mixed-reality technologies. Some prominent examples were already discussed in more detail in the preceding sections.

Recently, large-scale studies revealed that consumer applications form the largest component of the market in 2014, whereas non-consumer niche segments only account for about 35% of the overall market (Salah, et al., 2014, pp. 17-18). Over the next few years, this market-share structure is presumed to shift even stronger towards the consumer segment due to advancement in augmented reality technology and the expected growth of the included entertainment sub-segment (Rizzo, 2013; Grand View Research, Inc., 2016).

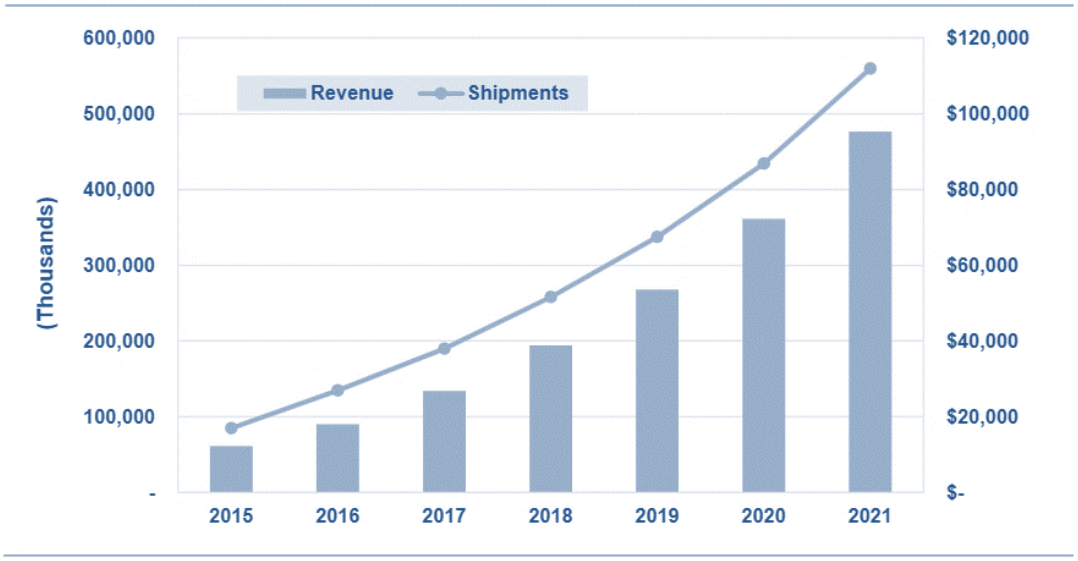

Figure 2.3: Total wearable technology shipments and device revenue from 2015 to 2021 (Source: IHS Markit, 2014)

However, one should bear in mind that the wearable market is highly dynamic in nature and expected to transform continually. Estimates concerning the development of the industry vary considerably as researchers have just commenced to grasp the wearable computing market (Salah, et al., 2014, p. 16). In addition, in most cases wearable

devices cannot be allocated clear-cut within a single end-user segment, as their functionality increasingly matures. The technological advances in the field entail a growing number of use cases, which touch multiple segments of the consumer market (Mobiquity, 2016). Also, new opportunities for business may emerge in the 'digital economy', which are not currently recognised (Mischke, 2012). Therefore, forecasts frequently vary with regard to projected numbers and definitions, and the future of the wearable technology market remains somewhat unclear. Nonetheless, the projected growth trajectory of wearables signals that there is a huge market potential. For instance, the market intelligence firm Tractica predicts a growth of total shipments of wearables from 85 million in 2015 to 560 million in 2021, which reflects a compound annual growth rate (CAGR) of 37% (Kaul & Wheelock, 2016). Figure 2.3 shows the forecasted total wearable device shipments and revenue in the global market. In a similar vein, IHS claims that driven by the increasing number of sensors in each product sold, the worldwide market for sensors in wearables will expand by a factor of seven from 2013 through 2019 (IHS Markit, 2014).

In spite of their potential, most wearable systems have not yet reached the European market. Compared to North American and Asia-Pacific regions, which together account for 70% of the global market, Europe holds only around one fifth of the wearables market (European Commission, 2016, p. 14). From a macro-level point of view, this might be explained by the fact that US-Europe differences in technology adoption and growth are often due to institutional rigidities and excessive regulation (Krueger, et al., 2003 p. 37). A recent study revealed that among the four major European smartphone markets in March 2016, Italy had the highest penetration rate with a total of 10.3 percent, followed by Great Britain (7.9%), Germany (5.4%) and France with 4.6% (Kantar, 2016). Penetration rates for other European countries are not available to date but are assumed to be on the same level or below. Figure 2.4 gives an overview of the results from this study.

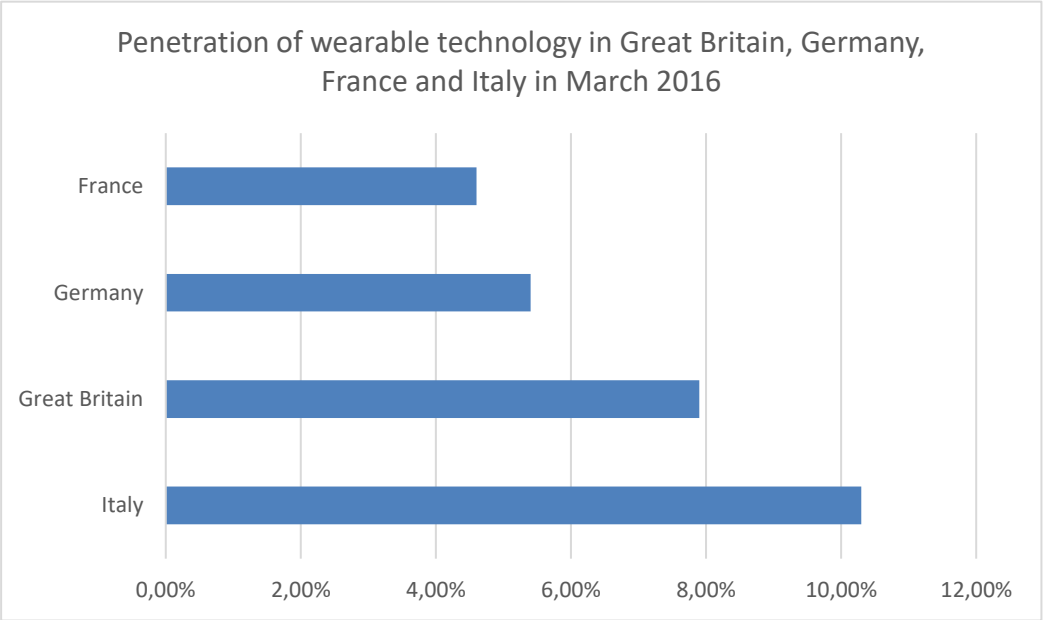

Figure 2.4: Penetration of wearable computing in four major European smartphone markets (Source: Kantar, 2016)

The assessment of sales statistics of preceding mobile device innovations such as smartphones and tablets poses another interesting point of comparison. At the end of the third quarter of 2014, the market research company

GlobalWebIndex interviewed more than 41,000 consumers in 32 markets including U.S., Canada, Brazil, the U.K. and China (Wagner, 2015). The firm reports that four out of five adults surveyed possess a smartphone, nearly half of them own a tablet, and almost 10% would use a smartwatch. Generally, adoption of wearables has grown in 2015 to around the same percentage as mobile tablet ownership was in 2012, i.e. about 20%. Global research firms therefore project the adoption curve of wearables to parallelise that of tablets (Bothun, et al., 2014; eMarketer Inc., 2015). However, it should be taken into account that after demand had peaked, sales of tablet computers had flatlined and, thereby, proved these technologies to be less popular than smartphones. While mobile phones have achieved s-shaped growth curves in mainstream markets, tablet-PCs still lack the breakthrough that leads towards full acceptance (Titcomb, 2017; Dediu, 2013). From this perspective, it is questionable whether wearable devices will experience the same market success as mobile phones. As Cathy Boyle, a senior mobile analyst, put it: "[…] manufacturers, specifically their marketing teams, have significant work to do in convincing the average person that a smart watch is as worthy of their time and money" (eMarketer Inc., 2015). In a high-tech context, many emerging technologies even fail to gain any relevant market share (Planing, 2014 p. 18).

When looking at individual device types, it appears that watches and wristbands are experiencing a steady growth since 2014 and are anticipated to remain the biggest market for wearables in the near term. In some literature, smartwatch adoption is even considered to be the first step towards commercialised wearables (Jung, et al., 2016, p. 899). Since many smartwatches are designed as peripherals to mobile phones, market analysts assume that it is particularly the proliferation of smartphones that acts as a 'complementor' in terms of the diffusion of wearable devices (Szopa, 2015, p. 236; Dahad, 2016). Also, the quantified self-movement is thought to have propelled the trend towards smart wrist-worn technologies (Salah, et al., 2014, p. 18). This specific movement describes the societal trend to self-track any kind of biological, physical, behavioural, or environmental information with the aid of wearable sensors for self-knowledge and self-optimisation purposes (Swan, 2013 p. 85). Overall, the vibrant wristwear market including smartwatches and wristbands is expected to grow at an annualised rate of 18% through 2021 to reach 70 million units sold (Beaver, 2016). Still, despite its steady growth, six months after the initial launch of the Apple Watch in the second quarter of 2015, the market for smart wristwear is witnessing a slowdown in sales ever since (Richter, 2016). Even worse, in the third quarter of 2016, the whole smartwatch market experienced a steep downturn, decreasing by 51.6% in its year-over-year growth (IDC 2016). This development is in line with prevailing forecasts on the sales figures of device types. Figure 2.6 shows the predicted global wearable technology sales by product category from 2014 to 2018. As can be seen, the growth of both smartwatches and smart wristband products is expected to stagnate from the year 2017 onwards, whereas smart glasses and other types of wearables are supposed to gain momentum as of this date. Yet, in regard to the smart watch category it should be kept in mind that the column displaying the estimation for 2015 also includes the launch of the Apple Watch.

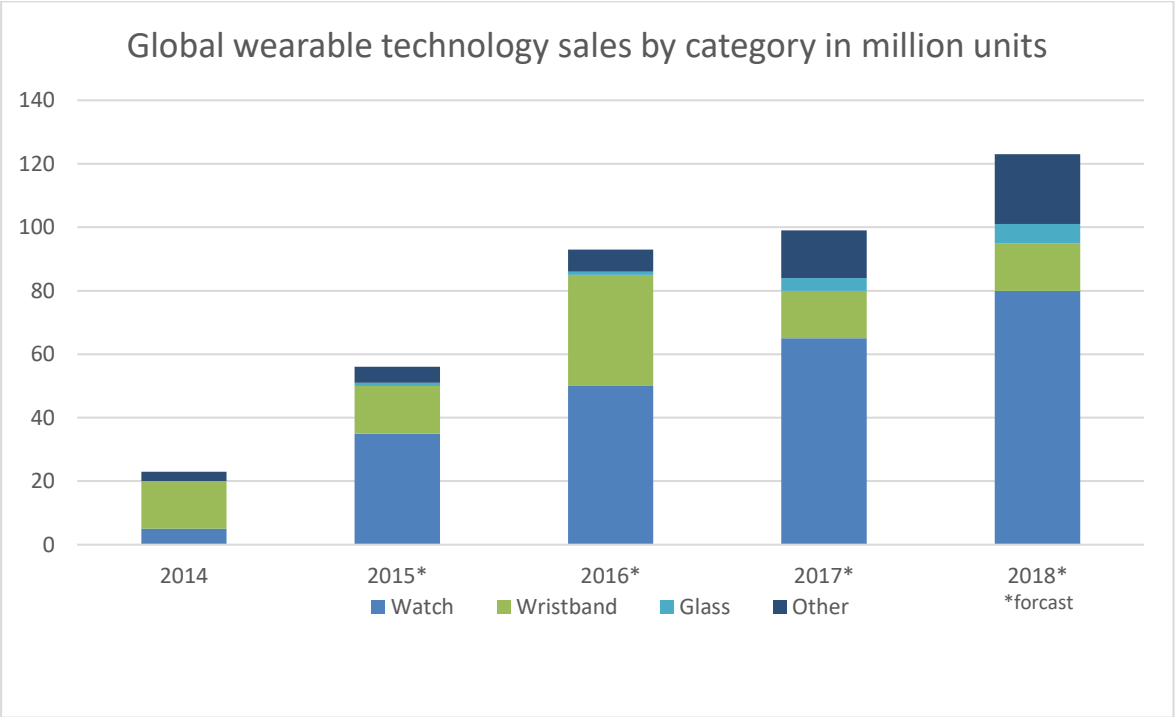

Figure 2.6: Global wearable technology sales forecasts by category from 2014 to 2018 (Source: IDATE, 2014)

According to the International Data Corporation (IDC 2016), the emergence of additional form factors that deliver new capabilities and experiences will be of significant benefit to the wearable market in the long-term. In particular, eyewear is expected to feature a CAGR of 201.2% from 2016 to 2020. Even though this specialised device type will account for less than 10% of global shipments by 2020, it is projected to account for more than 40% of the total revenue of the market due to the high prices (ibid.). Conversely, because of the early lifecycle stages of garment-based wearable products, the outlook for the smart clothing and fashion market is characterised by rather contradictory forecasts (e.g. Bonfiglio & De Rossi, 2010, p. 277; Kaul & Wheelock, 2016; Dalsgaard & Sterrett, 2014, p. 3). As with most early-stage markets, there is much commercial potential yet to be discovered. Smart clothes still need to find applications where they represent the most suitable solution to a need. Yet, even less clear are forecasts concerning smart jewellery, since market analysts tend to summarise all device types beyond wristwear, eyewear and clothing under a relatively ambiguous 'other'-category. The slow adoption is also manifested in a lack of public awareness (Hanuska, et al., 2016, p. 7). Figure 2.7 displays a global Internet search trend analysis on the key words 'smartwatches', 'smart glasses', 'smart clothes', 'smart jewellery' and 'smart shoe' performed in mid-2017 by setting the location parameter to 'worldwide'. Recent Internet searches show an overall increasing public popularity of smartwatches, whereas users still are largely unaware of smart jewelleries. While the first peak of interest in smartwatches in the fourth quarter of 2015 may be explained with the launch of the Apple Watch, the second peak at the end of 2016 might be attributed to seasonal demand and the introduction of the second-generation Apple Watch (Perez, 2017). This again underscores the strong impact of brand loyalty on product growth.

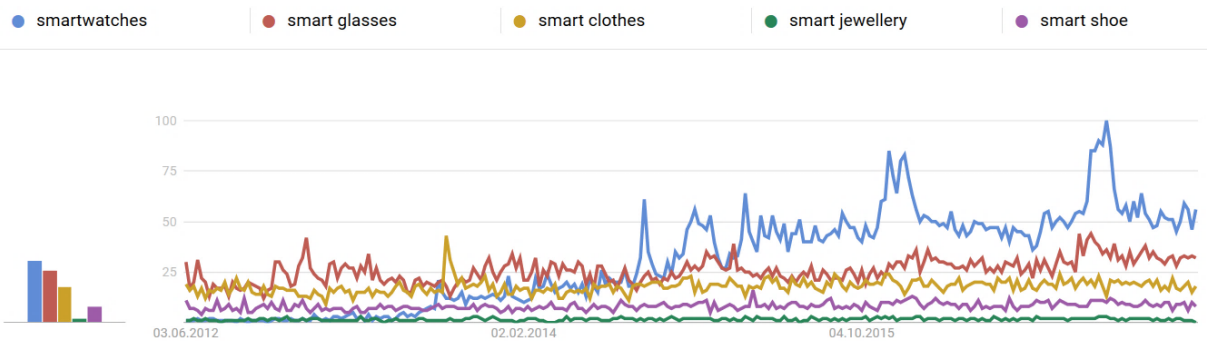

Figure 2.7: Google Trends analysis for the search terms smartwatches, smart glasses, smart clothes, smart jewellery and smart shoe (Retrieved on 01.06.2017)

A similar pattern emerged in a panel study among 2,407 consumers from different parts of the Asia Pacific region representing both developed and developing countries (Tsui, 2015). Figure 2.8 exhibits the study results. According to this study, consumers are most aware of smartwatches (86%), followed by smart glasses (69%) and smart wristwear (55%). The least prevalent item identified by respondents in their notion of wearable technology were e-textiles (20%). Nonetheless, such trend statistics should be viewed with due caution, since they are contingent upon the research setting and semantic issues such as word ambiguity and (multi-)lingual context (Kronberger & Wagner, 2000, p. 304). For instance, 'e-textiles', 'smart clothing' and 'smart shoes' can be synonymous in some research contexts but not in others.

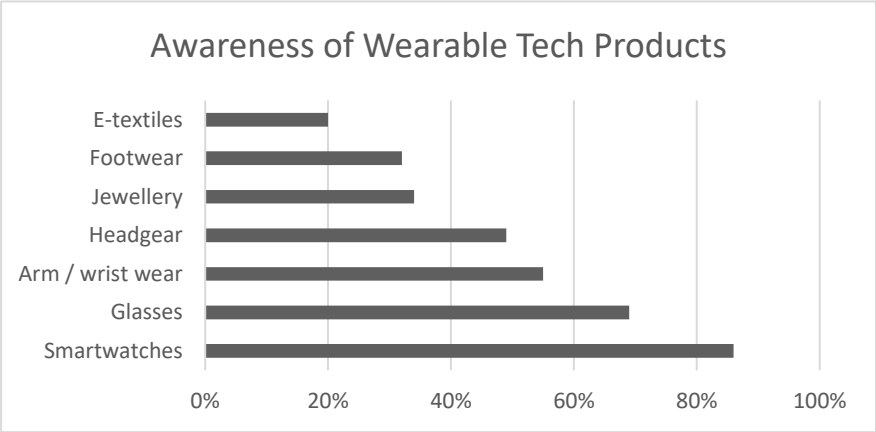

Figure 2.8: Consumer awareness of wearable devices in Asia Pacific regions (Source: Tsui, 2015)

Finally, with regard to the broad array of products of the wearable device market (horizontal differentiation) and the various quality levels (vertical differentiation), it is worth noticing that indirect **network externalities** are deemed to create severe barriers to entry for competitors (Wu, et al., 2016; Piana, 2003). A network externality (also referred to as positive network effect) is defined as changes in consumption benefit that an agent derives from a good when the number of other agents consuming the same or a compatible kind of good changes (Liebowitz, et al., 1995 p. 6). While direct consumption externalities are generated through the number of purchasers which directly affects the utility of a product (e.g. communication networks such as e-mail networks or fax machines), indirect externalities refer to *market mediated effects*. Hereby, the utility of a product increases with the greater availability of compatible, complementary products such as software for specific operating

systems or toner cartridges (Katz, et al., 1985 p. 424). This means that in any high-tech industry, the companies with a larger number of customers are more likely to offer and update complementary products and services. Especially in a wearable computing context, where devices are supposed to continuously gather and analyse personal information, the increased consumer data may be strategically utilised to provide additional services. For instance, by effectively analysing its large amount of customer data, "Jawbone has created a position of vice president of data so that to improve its product design" (Wu, et al., 2016, p. 3). Moreover, consumers may interact with more users as installed base increases, benefiting from more working experience and a wide availability of expertise.

2.5 Chapter Conclusions

While more traditional media channels such as Desktop or mobile computers has already spurred a lot of academic debate on conceptual and practical grounds, there is relatively little research available on the emerging wearable computing paradigm. From a theoretical perspective, wearable devices form a distinct and innovative type of ultra-mobile electronics in the highly dynamic IoT-world. Along a set of key attributes, a detailed characterisation of wearables was presented, which differentiates the new ICT paradigm from other Information Systems classes. It was established that compared to conventional mobile phones and portable computers, wearables operate even more naturally and effortlessly. In addition, a classification scheme was developed to enable the positioning of wearable devices in the market landscape according to identified core dimensions. The taxonomy was applied to several commercially available products, namely smartwatches, smart glasses, smart shoes and fitness trackers. Due to their general applicability, the former two technologies were discussed in greater detail.

Further on, the current situation of the wearable device market has been examined from different viewpoints to gain a more complete picture that accounts for the highly fragmented product landscape. The analysis revealed that there is a vast economic potential for such devices in the European market. Wearable computers might significantly spur the ICT industry, which is currently facing a slowdown of growth (Jung, et al., 2016, p. 899). But despite the positive prospects and their tremendous potential to disrupt a variety of different sectors, wearables are still niche products with low market penetration rates. The long-term stability and attractiveness of consumer segments has yet to be proven. In terms of public awareness, it has been demonstrated that consumers are most interested in smartwatches, followed by smart glasses. Particularly, the Apple Watch seems to have driven public popularity of the former product category over the last few years. In this context, it is fair to say that the increased interest may be attributed to brand loyalty rather than to a heightened demand for smartwatches in general. Up until now, however, surprisingly little is known about what impacts adoption rates of wearable computing beyond brand effects and research is needed to more comprehensively understand the differences in forecasts and sales figures of innovative mobile devices.

Among the numerous macro-environmental forces that affect the spread of an IT-based innovation, especially the issue of market acceptance and the way these technologies meet the wants and needs of potential users has long been identified as a pillar of marketplace success (Rogers, 1983; Davis, 1985; Hernandez, et al., 2009 p. 1241). Thus, manufacturers and retailers need to understand who the 'real-life wearable users' are and why they intend to use these new technologies in order to "establish a basis for evolving the market and tailoring it to a varied

audience to increase appeal" (GfK, 2017). In regard to the outlined network externalities of wearable devices, for the successful commercialisation of wearables it is particularly crucial to understand adoption behaviour in very early stages of diffusion and to reach a critical mass of users soonest possible.

Yet, in-depth knowledge of the consumers' beliefs and perceptions towards wearable computing is still lacking. There is no clear understanding of the drivers and obstacles to the early adoption of these technologies. To fill the gap, this thesis aims to shed light on the individual-level and cognitive factors that explain consumers' intention to use wearable technologies. The next sections therefore deal with the most influential behavioural theories that were adopted by a great stream of previous Information Systems research, specifically addressing issues with regard to innovation diffusion and user acceptance. The well-recognised theoretical frameworks and relevant concepts may provide researchers with a good starting point for understanding ICT usage intention formation.

3 Theoretical Foundations

This chapter aims at laying a solid foundation for the sought theoretical framework by reviewing relevant literature in the field of innovation acceptance. It synthesises different perspectives, important assumptions and key concepts in order to provide an understanding of the structure of the subject and to place the proposed study into the existing body of knowledge. The literature review thereby helps to frame and to justify the chosen approach and, moreover, demonstrates how the present research advances the available knowledge base in the area of interest (Planing, 2014 p. 27).

To increase efficiency of the literature review, it was based upon a concept-centric approach (see Webster and Watson, 2002). As opposed to the widespread author-centric approach, which primarily represents a summary of relevant articles, the concept-centric approach concentrates rather on taxonomies in which relationships between relevant concepts are considered. Given the identified need for a profound understanding of the underlying mechanisms that drive wearable computing adoption at individual-level (cf. chapter 2.5), this research focuses on the consumer *acceptance* of a technological *innovation*. Therefore, the two concepts 'acceptance' and 'innovation' particularly determined the organising structure of the review. In line with the operational understanding of the term 'acceptance' in the broad ICT adoption literature, for the present purposes acceptance is defined as a relatively enduring, positive attitude towards the use of a new technology (Gao & Bai, 2014, p. 215; Tuomela, 2000, p. 127). This definition accentuates the latent willingness to use a system, rather than the actual usage behaviour. It is conceptually closely related to the common definition of innovation adoption, which describes a process that starts with the initial awareness of an innovation and moves to product evaluation, then to the decision to try the adoption and finally to a "continued full-scale use" or repeat purchase decision in case of a non-durable innovation (Nabih, et al., 1997, p. 191; Wisdom, et al., 2015). For research economic reasons, measurement of the actual usage behaviour is not viable for the present study. Thus, the concepts acceptance and adoption are understood interchangeably as the *intention to use a technology* throughout this thesis.

3.1 Behavioural Theories

Prior research on wearable devices possesses largely a technical or application perspective (Hein & Rauschnabel, 2016, p. 86). For instance, researchers have already investigated diverse applications and several aspects of smart glasses in medical (e.g. Muensterer, et al., 2014) and industrial (e.g. Bauer, et al., 2016) settings. The few existing studies with a behavioural perspective mostly focus on specific product categories (e.g. Li, et al., 2016) and single base models (e.g. Chuah, et al., 2016). This *theory monism*, however, may not suffice to comprehensively explain a complex phenomenon in the field of social sciences and marketing research (Wübben, 2009, p. 51). Therefore, in the course of the present study an integrative approach is employed in order to frame a holistic as well as coherent system of hypotheses. Within this model of cause and effect chains, wearable technology acceptance is related to pervasive concepts in diffusion research (especially to key terminologies of innovation adoption) as well as to the field of Information Systems (particularly to empirical findings from technology acceptance research), to core principles of IT security, and to influential frameworks in personality psychology.

From an epistemological perspective, this research aims at synthesising commensurable theories from different research streams to create a comprehensive understanding of the consumer's adoption process. This multiple-theory approach is chosen, as the acceptance phenomenon was found by a multitude of empirical studies to be multi-causal in nature, depending on several interrelated drivers (King & He, 2006, pp. 740-741). Hence, combining different research streams may expand the explanatory and predictive power of a theoretical acceptance model. After all, considering several perspectives simultaneously allows to derive more holistic working propositions and, thus, to deepen the understanding of the phenomenon under investigation.

Furthermore, when choosing a multiple-theory approach it has to be decided whether to employ this methodological path in a pluralistic or eclectic fashion (Wessely, 2010, p. 9). A pluralistic approach combines different theoretical assumptions in their regular form, whereas an eclectic approach coherently unites partial aspects of multiple commensurable theories that span the theoretical layer of the scientific research. As Information Systems research includes various interlinked topics consisting of scientific disciplines as diverse as economics, psychology and sociology, an eclectic approach appears to be more fruitful for comprehensively analysing inter-individual acceptance processes (Leidner & Kayworth, 2006, p. 373; Hughes, 1998, p. 4). Especially the simultaneous need for both intrinsic, adopter-related and extrinsic, product-related predictors prompts the use of different streams of literature (Venkatesh, 2000, p. 343 ff.). Therefore, an eclectic paradigm was chosen as guiding principle for constructing the conceptual framework of the research study at hand. In order to identify a suitable source model as a theoretical mainstay for successive hypothesis formulation, this chapter critically reviews most influential and well-researched behavioural theories in sociology and social psychology against the backdrop of the present research subject. In particular, theories and concepts associated with the individual acceptance decision process as prime object of inquiry are approached in the following. Figure 3.1 gives an overview of the reviewed theoretical frameworks.

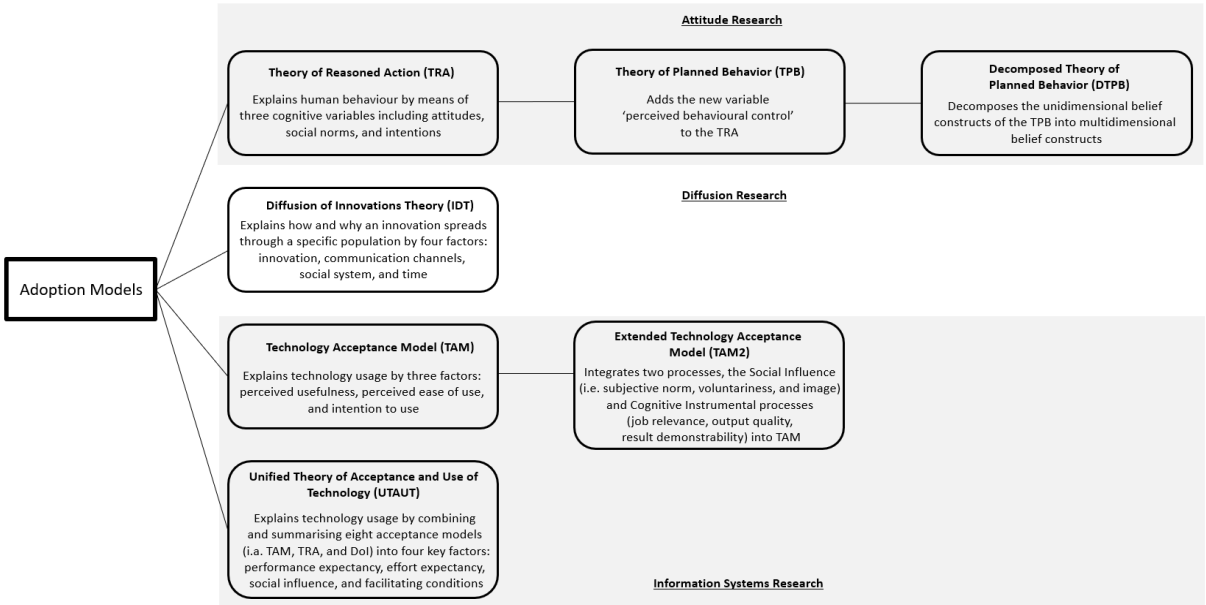

Figure 3.1: Overview of relevant adoption models

3.1.1 Innovation Diffusion Theory

Since 1962 the Innovation Diffusion Theory (IDT) by Rogers has tremendously influenced multiple disciplines including anthropology, rural sociology, communication, medicine, and education among others (McMaster & Wastell, 2006, p. 384). Particularly within the field of Information Systems research the formal diffusion theory has attracted considerable academic attention. In essence, diffusion is defined as a process of innovation dissemination within a given population through both mass media and interpersonal communication exchange (Rogers, 1983a p. 5). Diffusion is thus understood as a specific type of interpersonal communication, which implicitly signifies some degree of social change within a given population. Accordingly, innovation diffusion is a dynamic and time-attributed process, involving a gradual transfer of new information over a specified social system (Lechman, 2015, p. 30). Marketing research is particularly interested in the evolutionary process from the commercialisation of an invention turning into an innovation (i.e. market launch), to its large-scale diffusion within a consumer market. In general, this implicates a rather erratic and idiosyncratic trajectory path.

In the empirical literature, there is a broad consensus that the innovation diffusion process is fairly complex. It involves significant time lags due to varying adoption rates among the members of a given social system (Hoff, 2012 p. 33). It becomes apparent from the collected evidence in numerous exploratory surveys since the late 1950s (Kemper, 2009, p. 98) that in a stylised form the diffusion of a single innovation approximates formally a logistic distribution function: Assuming that the noncumulative adoption pattern follows typically a normal, bell-shaped curve indicating the frequency distribution of actual period-by-period adoption decisions, the innovation and diffusion process is commonly outlined as an S-curve that displays the cumulative demand of a novelty over time (Rogers, 1983a p. 23; Mahajan, et al., 1995 p. G82). By its very nature, the market potential indicates the market saturation level inherent to the system. Regarding the S-shaped curve phenomenon, the inflection point marks the transition from the convex (take-off) to the concave growth shape. Thereby, both the progressive proliferation among **innovators** (those with a constant propensity to adopt) and the degressive growth of **imitators** (those whose propensity to adopt is affected by the amount of previous adoptions) are represented by respective coefficients (Meade & Islam, 2006, p. 539; Bass, 1980, p. S56). Figure 3.2 illustrates the cumulative product growth together with the noncumulative adoption curve as a function of time. Almost all basic mathematical descriptions of innovation diffusion (in particular, the most frequently applied sigmoidal model by Bass) were established up to the 1970s. The main modelling developments from this date onward have mostly been slight modifications of the existing functions. These extensions aimed to add greater flexibility to the existing models, for example by means of auxiliary marketing mix variables (e.g. pricing and promotion) in the model parameterisation. Further variants focused on a generalisation of the base models, taking into account different diffusion stages in several countries or successive generations of technologies (Meade, et al., 2006 p. 520 f.). Still, the bulk of those contributions addresses the explanation of past behaviour rather than predicting future behaviour (ibid.).

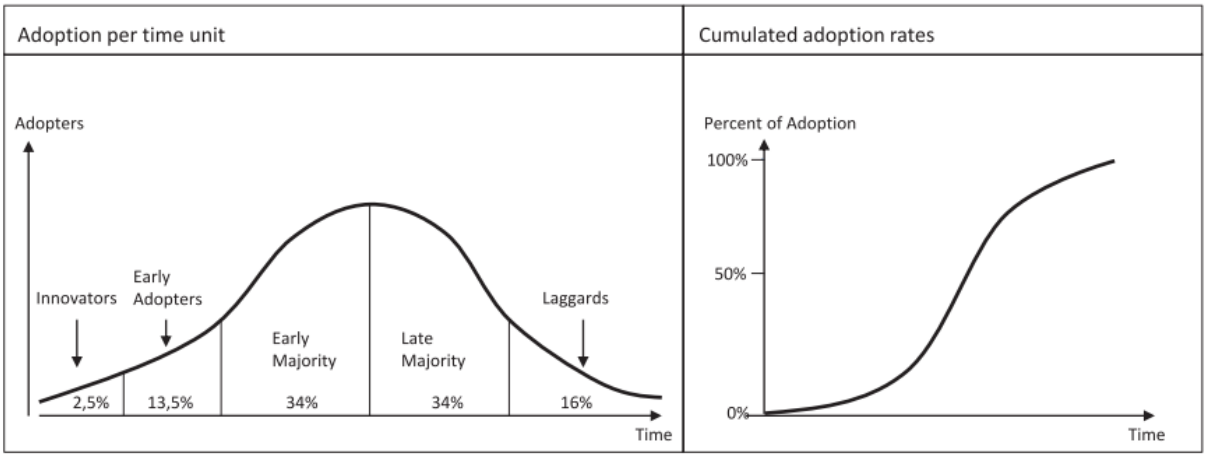

Figure 3.2: Diffusion of innovations and adopter categories (Planing 2014, p. 37)

In view of the most fundamental drivers of the innovation and diffusion curve, Rogers declared that "diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system" (1983, p. 5). This widely recognised definition subsumes in essence four constitutive key components of the diffusion process:

a) **Innovation**. In his entrepreneurial theory of capitalism, Schumpeter (1939) was the first to introduce this term within the economic environment. Conceptually, innovation is defined as "doing things differently in the realm of economic life" (1939, p. 84). However, up to now, a universally accepted, generic definition of this concept is non-existent in the academic literature. Instead, depending on the prevailing disciplinary perspective there are divergent conceptions (Baregheh, et al., 2009, p. 1324). For instance, literature on human resource management, entrepreneurship, Information Technology, engineering, and marketing discusses the term variously. While there are some definitional overlaps between the different disciplines, an authoritative definition is lacking yet. Rather, there are several approaches that can be classified as firm-oriented, product-oriented, market-oriented and consumer-oriented definitions (Schiffman, et al., 2009 p. 437-439). The firm-oriented approach judges the novelty of an innovation in terms of its newness to the company, which implies that the actual market penetration rate of a novel product, service or idea is disregarded. The market-orientation, on the other hand, regards 'innovation' solely from a market perspective in terms of the degree of exposure consumers have to the novelty. By contrast, the product-oriented definition emphasises the influence the new product qualities have on the consumer's habituated consumption behaviour. In order to classify the innovative content of a novelty, the extent to which it disrupts behavioural patterns is usually taxonomized by the classes *continuous*, *dynamically continuous* and *discontinuous innovations* (also referred to as *disrupt* or *radical* innovations). In view of the progression of computing devices towards more ubiquitous information systems - from mainframes to desktops to laptop PCs and ultimately to mobile phones and smart wrist watches - current wearables can mostly be attributed as *dynamically continuous innovations* from a product-oriented perspective of innovation management (Schiffman, et al., 2009 p. 437). This means that consumers do not have to adopt completely new behavioural patterns in order to employ wearable technologies appropriately as in the case of radical innovations. Instead, considering the relative newness in form and features, consumers have to slightly accommodate habituated usage patterns. For example, smartwatches are not essentially new

products compared to the functionality of smart phones, but they offer a new channel as well as novel modes of interaction. From a marketing perspective, the prevalent consumers' consumption habits have to be modified by 'educating' potential adopters about the relative benefit of the wearable product in order to stimulate primary demand within the introductory stage of the product life cycle (Pride & Ferrell, 2015, p. 492).

b) **Communication channels**. According to Rogers, the rate of innovation adoption is, inter alia, basically determined by the efficiency of the respective means for information exchange within a homogenous group of potential adopters (Rogers, 1983a pp. 17-18). These communication channels include both mass media instruments and interpersonal communication. As per prior empirical findings, word-of-mouth or informal personal communication are the most effective means for persuading individuals of a referral social network, whereas mass media channels are more efficient in creating awareness-knowledge (ibid.). More precisely, research findings suggest that interpersonal communication moderates the effects of mass media considerably by reinforcing recognition memory for the content in question (Southwell & Yzer, 2007, pp. 443-445). However, in order to develop communication initiatives appropriately, a thorough knowledge of the social context concerned is finally vital for choosing the most effectual instruments (McLeod & Vaughan, 2014).

c) **Social system.** This key element of diffusion refers to societal microstructures featuring a high degree of homogeneity. A social system may include individuals, informal groups, organisational units, and subsystems, where system members are alike among each other in certain attributes, such as beliefs, education and social status (Rogers, 1983a p. 24). The level of homogeneity of a social network essentially determines the rate of adoption. However, it must be emphasised that the classical diffusion theory rests on the implicit assumptions that a) an innovation should be diffused more rapidly and adopted by all system units, regardless of possible anti-diffusion programs (**pro-innovation bias**) and b) there are generally no user interdependencies (Fichman, 1992 p. 195-206; Perner, 2013; Rogers, 1983a p. 92).

   Particularly, the latter assumption is frequently violated in practice as technological innovations are by nature often subject to network externalities and organisational rules. The emerging value chains of wearable devices enable new business models not only for manufacturers, but for all inter-organisational partners, occupying a position within the chain (Rizzo, 2014). Such indirect network externalities are self-evidently the case for software and hardware vendors whose interoperable applications and convergent technologies mutually influence the technological trajectory of wearables. Nonetheless, despite the fact that network effects may accelerate mass-market adoption, for achieving a breakthrough penetration rate where the diffusion curve becomes self-sustaining, consumer acceptance is deemed the most important prerequisite (Davis, 1993, p. 475; Kleijnen, et al., 2009, p. 344).

d) **Time**. The time dimension is fundamentally intertwined with the concept of diffusion at three descriptive, interrelated levels (Rogers, 1983a p. 20 ff.):

   (1) From a micro-level perspective, diffusion is a multistage decision-making process that encompasses five linear stages through which a message receiver goes. Roger's phase model essentially depicts information-seeking and information-processing activities for reducing uncertainty about the anticipated consequences of the adoption or rejection of an innovation (Planing, 2014 p. 38; Rogers, 1983a p. 163).

In the initial phase of **knowledge**, the individual or decision-making unit takes a relatively passive role when developing awareness of an innovation and when gaining a substantial understanding about its meaning and utility. However, individuals tend to expose themselves to communication messages that are consistent with their existing predispositions, such as interests, needs and attitudes. Likewise, people are generally inclined to interpret new information in terms of available beliefs, what is referred to as *selective perception* (Rogers, 1983a p. 166; Choi, et al., 2010 p. 58). Some scholars therefore underline the relevance of the so-called 'problem-recognition' stage, which precedes the creation of awareness knowledge (Schiffman, et al., 2009 p. 463).

At the subsequent **persuasion** stage of the innovation-decision process, individuals form an affect-laden attitude towards the innovation in the sense of favourability or unfavorability. The individual is hence more sensitively involved with the innovation, actively seeking information by means of perceived innovation characteristics to reduce uncertainty about the expected consequences of adoption. According to Rogers, the implementation of an innovation is, *ceteris paribus*, relatively likely if the five product-related adoption factors are perceived to be salient (Rogers, 1983a p. 15 f.): (1) relative advantage (2) compatibility (3, reverse) complexity (4) triability, and (5) observability.

The *relative advantage* criterion broadly denotes a superior alternative in technological, economic, social or emotional terms. This factor also comprises anticipated behavioural consequences towards personal goals (Planing, 2014 p. 39). *Compatibility* refers to the degree to which an innovation is congruent to either behavioural patterns and values or existing experiences and practical needs of the potential adopter. *Complexity*, on the other hand, relates to the extent to which an innovation raises cognitive efforts. Further, *triability* is the degree to which the innovation is perceived as available for trial on a preliminary basis. Finally, the *observability* characteristic relates to the communicability of the innovation's utility and benefits. However, only the first three innovation criteria were found to be significant adoption correlates (Tornatzky, et al., 1982 p. 40 f.). Moreover, some authors question the dimensionality and thus the simplified operationalisation of the theorised relative advantage construct, since it reflects a multidimensional attribute, whilst the relative importance of its underlying facets is strongly context-dependent (Dekimpe, et al., 2000, p. 29).

The third behaviourally relevant subprocess, i.e. **decision**, relates to the mental state change from indifference towards the object of adoption to its adoption or rejection. Herein, the concept of adoption describes an attitudinal construct that is directly determined by evaluative judgements. When an individual decides to put an innovation into practice, the **implementation** stage follows, what apparently involves an overt behavioural change.

Eventually, **confirmation** occurs when an individual seeks to avoid or reduce a state of internal disequilibrium or dissonance by reinforcing the respective innovation decision. However, in case of conflicting information the decision-making unit may also reverse the previous decision.

(2) As personal characteristics are thought to determine the diffusion time path significantly, the second dimension refers to the degree of innovativeness, i.e. the extent to which a decision-

making unit is early in adopting new ideas compared to the social frame of reference. According to their innovativeness in terms of a classificatory principle, Rogers segments the members of homogenous social systems into five mutually exclusive and collectively exhaustive categories (Rogers, 1983a p. 245 ff.): The first individuals to adopt an innovation are referred to as *innovators* (approximately the first 2.5% of all adopters), followed by the *early adopters* (the next 13.5% of adopters), the *early majority* (the next 34%), the *late majority* (the next 34%) and the *laggards* (the last 16%). Under the influence of innovators and early adopters, who play a catalyst role for mass-market development, imitative consumers should become the main actors in the diffusion process to achieve market penetration more quickly (Kim & Sim, 2012, p. 247).

(3) Finally, the rate of adoption reflects the relative speed with which an innovation is adopted by the members of a given population (Rogers, 1983a p. 23). Plotting the number of adopters on a cumulative frequency basis over time, most frequently the above outlined S-shape results. Nonetheless, crucially depending on the nature of the innovation acceptance context the product growth may show a different pattern resulting e.g. in more gradual or steeper slopes of the S-curve. Thus, it must be noted that the proposed theoretical model neither holds for all innovations (such as technology generations) nor for successive technologies (Hoff, 2012 p. 29).

In summary, diffusion is basically a macro-level process reflecting the dissemination of an innovation within a social reference system. Hence, macroscopic diffusion models provide parsimonious and analytically tractable ways to forecast demand growth of innovative consumer durables as well as to study whole markets and interpret their behaviour (Bass, 1980, p. S51; Laciana, et al., 2013, p. 1873). However, due to its model-inherent simplicity and universality the diffusion paradigm has also been subject to various criticism. One methodological criticism addresses the lack of explanations for the inflection points indicating the transition from progressive to degressive demand growth (Golder, et al., 2004 p. 207; Hoff, 2012 p. 30). This clearly decreases the predictive value of the model and reduces empirical implications that can be derived for the purposes of proactive product management. Furthermore, some critics argue that the diffusion process is not linear, but rather more complex, comprising feed-back loops and interdependencies between the well-defined development stages. In addition, product growth is influenced by various demand factors at the same time, such as social acceptability and changes in beliefs (Mehta, 2002, p. 270; Golder & Tellis, 1998, p. 260). Most importantly, such aggregated models are neither capable of providing insights about the internal processes that determine adoption decisions nor able to reveal how individual-level market interactions are tied to global market behaviour (Muller & Mahajan, 2010, p. 93). As recent research on social networks has rightfully questioned the assumptions of homogeneity and perfect mixing underlying aggregate diffusion models, diffusion research has increasingly broadened its scope from the aggregate level to an individual-level perspective (ibid.). For instance, one well-recognised microlevel approach is agent-based modelling, wherein individual adoption decisions are determined by decision rules including techniques such as neural networks and cellular automata. However, the relax of the above premises at the expense of an increase of model granularity entails inevitably computational costs which in turn limit sensitivity analysis and model scope (Rahmandad & Sterman, 2008, p. 998). In particular, individual-level data for describing disaggregate details of market dynamics are less available than market-level data (Laciana, et al., 2013, p. 1873). Ultimately, disaggregated micro-level models require complete knowledge of agent-agent relationships as well as sufficient

information on the influence probability between two neighbouring adoption units. Due to information privacy and data non-availability reasons, knowledge concerning both the detailed network structure and probabilities in wearable technology markets is yet scarce (Quinn & Brachmann, 2015; Schooler, 2014; Luu, et al., 2012, p. 218). Regarding the present research scope both aggregate and individual-level diffusion models thus appear to be inappropriate for validly explaining and predicting consumer acceptance towards wearable computing devices. As this research project focuses on an integrative approach to holistically conceptualise wearable technology adoption in detail, the empirical findings and theoretical insights of social psychology and Information Systems research are approached in the following.

3.1.2 Behavioural Theories in Attitude and Acceptance Research

According to the assumption of the widely acknowledged *stimulus-organism-response* (S-O-R) paradigm, environmental stimuli induce affective and cognitive reactions. These reactions in turn engender specific behaviours, particularly approach or avoidance responses towards a given trigger (Mehrabian & Russell, 1974, pp. 3-4). Thus, contrary to the standard neoclassical axioms of rationality (i.e. rigorous utility maximisation as well as completeness, transitivity and consistency in consumer's preferences), overt adoption behaviour is substantially determined by intervening internal states (Goodwin, et al., 2015, p. 178). In the context of information systems adoption, the most contributing internal factor for acceptance behaviours is the **attitude** towards the object in question (Davis, et al., 1989 p. 983; Rogers, 1983a p. 36). Therefore, the attitude-behaviour relation along with its underlying theoretical framework is discussed in-depth in the next section.

3.1.2.1 On the Attitude-Behaviour Relation

In general, the concept of behavioural attitude refers to an evaluative judgement on a bipolar continuum in terms of the overall favourability of a psychological object. Accordingly, Ajzen and Fishbein (1975, p. 216) describe attitude in their seminal work as "an individual's positive or negative feelings (evaluative affect) about performing the target behaviour." In conclusion, an attitude reflects a learned predisposition or tendency to respond towards an object or situation, producing consistency in verbal and physical behaviour and thus possessing a directional quality (Churchill & Iacobucci, 2010, p. 234). In marketing literature, this concept is one of the most pervasive notions as attitudes are deemed to directly influence consumer behaviour by connoting preferences and object evaluations (ibid.). This implies that behavioural intention fully mediates the effects of attitude on behaviour, which in fact has been frequently demonstrated by numerous earlier studies (Bagozzi, et al., 1990 p. 46). From an innovation diffusion perspective, attitude is conceptually closely related to – and hence commonly equated with – the acceptance or adoption decision (Davis, 1993, p. 477).

As a *latent*, i.e. hypothetical construct, this behavioural predisposition represents a not directly observable variable that must be deduced from measurable responses. These responses reflect positive or negative net evaluations of a given attitude object. They therefore constitute an instrument for predicting and explaining volitional human behaviour (Ajzen, 2005, p. 3). However, despite the fact that the attitude construct has widely been employed as a learned, affect-based response (Pyun & James, 2011, p. 35), the concrete intra-attitudinal structure is still subject of an ongoing intense debate (Bakker, et al., 2014, p. 416; Fiske, et al., 2010, p. 355; Bagozzi & Burnkrant, 1979,

p. 295; Petty & Brinol, 2010, p. 217): According to Fishbein's **expectancy-value** (EV) model, a person's overall attitude is substantially determined by salient beliefs (Fishbein, 1967, p. 257–266). Subjective beliefs are understood as the person's strength of belief that the behaviour in question will lead to the respective consequence, weighted by the subjective value of each consequence. More formally, a compensatory value judgement can be described as:

$$A = \sum_{i=1}^{n} b_i \, e_i \tag{3.1}$$

where A is the attitude towards a given object, b_i is the strength of belief that the attitude object has attribute i (in terms of a subjective probability), and e_i is the evaluation of attribute i (i.e. its desirability or emotional valence).

Nevertheless, critics argue that these predictors essentially comprise ordinal information. More specifically, empirically obtained ratings are often not proportional to the true subjective values (van der Lans & Heiser, 1988, pp. 1-4). Thus, the multiplicative interaction of cognitive beliefs and desirability may lead to invalid results given the error terms for both, at best interval-scaled measures without a true rational zero point. The cognitive variables, which already received weights, get multiplied with a motivational component and thereby inflated. This might introduce systematic error of unknown magnitude into the resulting product term (Davis, 1993). Beside this, beliefs about certain attributes are often correlated in product evaluations (Youjae, 1989 p. 71). From a nomological net perspective, the algebraic conglomeration of attitudinal components has also strong confound effects on dependent variables (Sheth, et al., 1974 p. 3; Bagozzi, 1984 p. 59). Therefore, the predictive validity of EV models of attitude can be considered as empirically ambiguous. Against the backdrop of this – yet ongoing – scoring controversy, an 'evaluative-belief structure' in the above sense of compensatory rules for attitude measurement seems to be less reasonable. Moreover, the methodological assumption that subjective expectancies equal objective probabilities appears inappropriate since subjective probabilities have proven to possess other integral features. For example, individual's probabilities are not expected to sum to 1 (Hewstone & Young, 1988, p. 959; Ajzen & Fishbein, 2008, p. 2228; Ahtola, 1975, pp. 52-59). This is deemed to be due to cognitive biases, replacing the laws of chance by judgmental heuristics such as the cognitive availability or representativeness of relevant outcomes (Kahneman & Tversky, 1972 p. 431). Furthermore, in comparison to self-stated expectancies (i.e. cognitive beliefs), statistically estimated weights via regression models yield more robust results as could be shown by several IT adoption studies (Davis, 1993, p. 477). Most importantly, the hypothesised nature of attitude as a function of the cognitive belief system is maintained in a decomposed model, what is clearly suggested by social psychology literature (Breckler & Wiggins, 1989, p. 253). The current study follows this view, that the attitudinal disposition and its inherent evaluative belief system are conceptually different constructs.

In regard to the dimensionality of attitude, there are two major conceptualisations referred to as the single component and multicomponent model of attitude (Bagozzi & Burnkrant, 1979, p. 295; Bagozzi & Burnkrant, 1980, pp. 339-344). The former perspective considers attitude to be a quasi-atomic, unitary construct, representing the affective response towards a given psychological stimulus. In accordance with Fishbein (1967), this mediating mental state can be directly inferred from people's beliefs and placed on a dimension ranging from favourability to unfavorability. Nonetheless, convincing empirical evidence in respect of the validity of the single component concept is still missing, not least because of the lack of relevant psychometric properties in many earlier used

measures (Bagozzi, et al., 1979, p. 88; Millon, et al., 2003, p. 303; Petty, et al., 1997, p. 614). Assuming this single factor conceptualisation of attitude, available study results differ significantly on the explained portion of variance in behaviour (Zhou, et al., 2013).

Another perspective, the two-component attitude model, argues that attitude is a more complex, multifaceted construct. It derives from affective and cognitive components, each based on distinct theoretical sources of information. As per this dyadic model of attitude, the cognitive component relates to the knowledge, thoughts and descriptive beliefs of an individual regarding the attitude object. On the contrary, the affective component involves feelings of like or dislike as well as emotions associated with the behaviour or object in question. From a factor-analytical view point, both the cognitive and the affective attitudinal facets are captured by distinct indicators. Notably, the affective constituent relates to connotative evaluations, whereas cognition rather adheres to denotative qualities of the reference object (Maler & Vincent, 2005, p. 949). The relevance of this attribution is especially apparent from a marketing context, where the functional utility of a product derived from its physical attributes (i.e. denotative features) is clearly distinguished from its symbolic benefits (i.e. connotative features), which relate to needs of the psychological and social environment (Kocak, et al., 2007, p. 161). Both attitudinal properties form the overall evaluative judgement, i.e. a distinct layer of explanation for the consumer's behaviour. They fully describe the composite construct and, in doing so, the very nature of the attitude concept.

However, multiple empirical studies have shown that the relative weight of **affect** versus **cognition** varies considerably depending on the nature of behaviour in question (Crites, et al., 1994, pp. 619-620; Zhou, et al., 2013). Specifically, focussing on the degree of personal relevance that the object of thought holds for the message recipient, Petty et al. emphasise the influence of consumer's **involvement** on attitude formation (Petty & Cacioppo, 1979, pp. 1915-1926). According to their well-recognised dual-process theory of attitude change, the *elaboration likelihood model* (ELM), there are two pathways of cognitive processing: the **central** and the **peripheral route**, which are understood as different poles of an elaboration continuum to process persuasive messages. The first route of persuasion involves high-effort scrutiny of the given attitude object by means of a more elaborate, conscious information processing. This corresponds to a cognitive attitude formation and prerequisites a high degree of involvement (Tam & Ho, 2005, pp. 287-290; Petty & Cacioppo, 1986, pp. 144-148). Hence, when elaboration likelihood is high, the degree of attitude change strongly depends on the quality of arguments relevant to the attitude object. On the contrary, when the peripheral route is activated, judgement formation is tied to affective associations or inferences based on contextual persuasion cues. Attitude is rather evoked by heuristic assessments and, thus, primarily affectively based. Consequently, under low involvement conditions secondary inducements (such as free samples or attractive packaging) are more important in the construction of attitude. Such peripheral cues are most likely to evoke an affect-laden information processing.

In light of its impact on attitude-behaviour consistency, a growing body of acceptance literature considers the level of emotions and feelings attached to a given object to be a central criterion in attitude formation. The emotional dimension should therefore play a key role in the design of persuasive communication instruments (Zhou, et al., 2013; Yang, et al., 2004 p. 19-21; Schiffman, et al., 2009 p. 292-293). By addressing this issue, many researchers emphasise solely on affective experiences and, thereby, completely neglect cognitive aspects in judgmental processes. But whether a single factor or a two-factor approach of attitude is more suitable depends ultimately on

the properties of the subject under investigation (Yang & Yoo, 2004, pp. 19-31; Davis, et al., 1989, p. 17; Davis, et al., 1989). Given that dynamically continuous innovations like smartwatches intrinsically introduce novel properties and, furthermore, carry a certain amount of purchase risk (Lantos, 2015, p. 309; Kuester & Hess, 2009, p. 783; Labay & Kinnear, 1981, pp. 271-278; Debevec, et al., 1985, p. 273), adoption likely involves a more elaborate information processing. In conclusion, a differentiation of attitude according to its cognitive and affective content appears to be appropriate for the present study.

According to the prevalent tripartite model of attitude structure, attitude manifests in a third component: the conative component. **Conation** refers to the behavioural domain of a person's attitude, i.e. it reflects the behavioural intention towards an attitude object. This action-oriented constituent is based upon the cognitive and affective dimension and represents prescriptive (i.e. normative) beliefs (Lantos, 2015, pp. 503-505; Vaughan & Hogg, 2013, pp. 136-138). In consumer and Information Systems research, this component is often treated as the consumer's *intention to buy* or *intention to use*. The interaction of the three attitude dimensions determines the consumer's consumption behaviour as illustrated in Figure 3.3. This tricomponent attitude model emphasises the ancient trichotomy of human experience divided into thought, feeling and action. Therein, both cognitive and affective facets of attitude mutually span the feature space of the evaluative construct (i.e. the consumer's overall evaluative judgement). The conative component, in contrast, constitutes an empirically as well as conceptually separate attitudinal construct. Still, it should be noted that the validity of the attitude-behaviour relation strongly varies under different conditions and contexts (Glasman & Albarracín, 2006, p. 778).

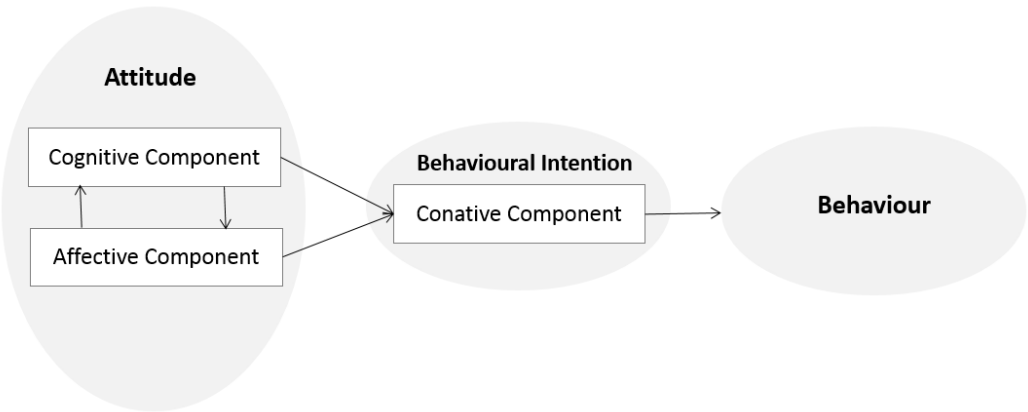

Figure 3.3: Structural model of attitude according to the three-component theory (Based on Breckler, 1984 p. 1192)

Firstly, the degree of specificity of both the attitudinal predictor and the behavioural criterion must correspond in terms of their inherent qualities *time*, *target* and *context*, otherwise a low attitude-behaviour correlation may result (Ajzen, et al., 1977 p. 889; Fazio, et al., 1978 p. 399). That is, the specificity of a measured attitude must meet the same level of specificity of the attitude-relevant action in order to maximize the predictive power of evaluative judgements. This precept is commonly referred to as **correspondence principle**. Secondly, with respect to the structural properties of attitude, many research endeavours have been – and still are – devoted to the concept of **attitude strength**. This concept is typically construed as the intensity and consistency of intra-attitudinal

components. By definition, attitude strength results in both attitudinal resistance towards environmental influences (especially persuasion) and a high degree of correspondence between the object evaluation and the subsequent overt action (Chaiken, et al., 2014, p. 388). In other words, strong attitudes are more likely to manifest behaviourally than weak and they are more stable as well (Ajzen, 2001 p. 38). According to Fazio, attitude strength is primarily indicated by the accessibility of object-evaluation associations from memory (2007, p. 2ff.). Thus, the strength variable is best approximated by the latency between the recipient's perception of the attitude object and the retrieval of the pertaining evaluative knowledge (Fazio, et al., 1982, p. 341; Fabrigar, et al., 2014, p. 88). Notably, personal involvement towards a specific behaviour is deemed to be an important aspect of attitude strength. It amplifies the sensitivity to pertaining stimuli and thus leads to a greater attitude-behaviour correspondence (Pomerantz, et al., 1995, p. 408).

Following the above line of reasoning, formation of attitude essentially means absorption and assimilation of more or less conflicting knowledge (thus available information) in pre-existing mental structures. Festinger's theory of **cognitive dissonance** accordingly postulates that individuals experience a state of psychological tension if they perceive contradictory information that oppose existent cognitions (Festinger, 1962). As humans latently strive for internal consonance, perceived inconsistencies among cognitive, affective and conative components cause to intensify this aversive tension state. There are substantially three strategies of dissonance reduction, whereby the pressure of implementing these modes inherently covaries with the magnitude of dissonance. The first approach rests upon changing salient dissonant elements *a posteriori* including attitudes, beliefs and behaviour. The second strategy consists of developing consonant cognitions that temper the perceived psychological discomfort. The third mode of dissonance reduction relates to the mitigation of the importance of incompatible cognitions, what is also referred to as *trivialisation* in social psychology literature (Greenberg, et al., 1995, p. 247).

Especially under such conditions where attitude strength is well-marked and the specificity of the attitude construct greatly corresponds to the behavioural measure, the cognitive dissonance paradigm provides a profound as well as empirically supported theoretical substantiation for explaining positive correlations between cognitions and actions. Still, attitude (in the above sense of a latent variable inferred from consistency in behaviour) is a necessary, but not sufficient condition for subsequent consumption behaviour. Rather, some portion of variance in overt behaviour has to be explained multicausally under consideration of further significant parameters. On account of that, much research has been done in order to holistically understand intention behaviours and to accurately explain decision-making in the context of accepting or resisting innovations. In view of their thematic relevance, the most influential behavioural theories, constructs, and explanatory models in attitude and Information Systems research are presented and critically discussed in the following section.

3.1.2.2 Theory of Reasoned Action and Competing Variants

The **Theory of Reasoned Action** (TRA) roots in social psychology and was initially introduced by Martin Fishbein and Icek Ajzen in (Ajzen & Fishbein, 1975; Ajzen, et al., 1980). Occupying a central position in the field, this theoretical model seeks to comprehensively analyse volitional human decision processes. To this end, the model particularly focusses on behaviourally-relevant latent variables in a stimulus-organism-response interpretation. Due to its integrative nature that links different research disciplines (e.g. learning theory and

information processing), TRA is applicable to a variety of subject areas in a highly generic manner (Ming-Shen, et al., 2007, p. 297; Deepti, et al., 2014, p. 30; Ajzen & Fishbein, 1975, p. 21 ff.). One of these application fields is Information Systems research. Contrary to alternative lines of research, which hold a constructivist position by implicitly presupposing unconscious automatisms and habitualisation, TRA is based on the meta-theoretical assumption of rationality and goal-directedness in human decision making (Caputi, et al., 2009, p. 499).

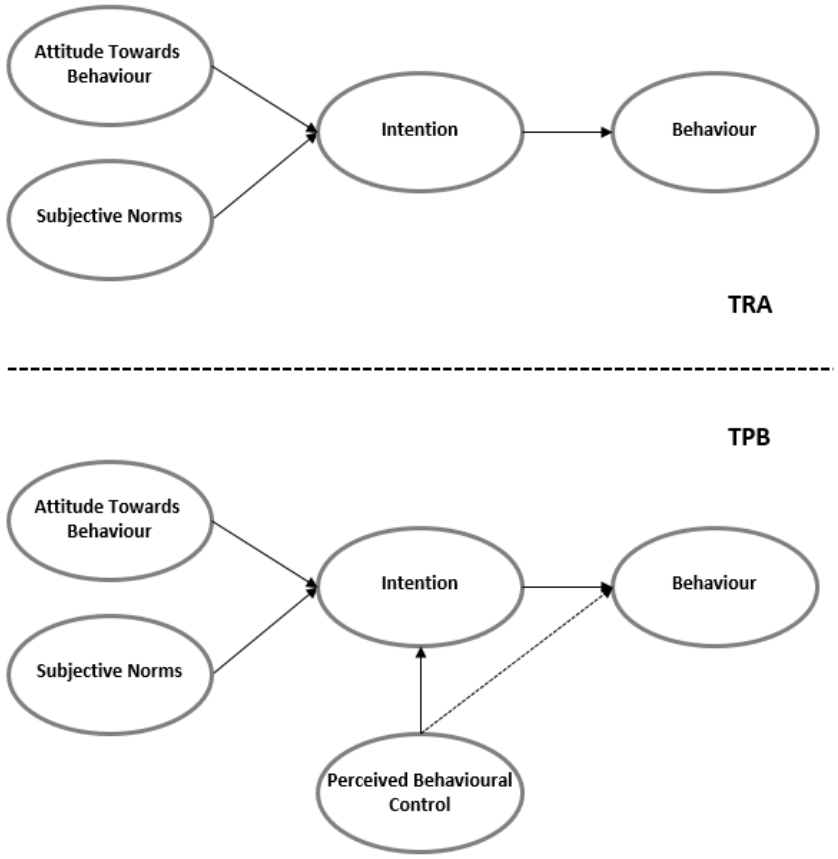

Figure 3.4: Path models for the theory of reasoned action (TRA) and the theory of planned behaviour (TPB) (Based on Fishbein 2008, p. 838, and Ajzen 1991, p. 182)

This conceptual framework suggests that the *behavioural intention* of an individual to perform a specific action (in terms of conation) is a proximal determinant of behaviour. Again, intentions and actions are deemed to be strongly related if measured at the same level of specificity (Fishbein & Ajzen, 1975, p. 289). TRA postulates further that the conative component is causally linked to both a personal (individual influence) and a social factor (normative influence). Relying on an expectancy-value formulation (as delineated in 3.1.2.1), the first hypothetical construct is considered to be a function of (*a*) salient (primary) beliefs about perceived positive or aversive consequences of performing the target behaviour and, furthermore, (*b*) the person's evaluation of these outcomes. These salient beliefs are unique to each attitude object and so each new stimulus situation again requires the elicitation of an individual set of behavioural belief statements (Ajzen, 1991, p. 192). Hence, attitudes are understood as composed, affect-laden responses. In contrast, the 'subjective norm' concept refers to a function of normative beliefs that one complies with the supposed expectations of the relevant social environment (Ajzen &

Fishbein, 1975, p. 302). That is to say, such belief systems capture the perceived social pressure to behave in a certain way. As stated by Ajzen and Fishbein (1975), variables external to the model are mediated exclusively by either attitudes or subjective norms. The overall scheme of TRA is displayed in Figure 3.4.

Considerable evidence supporting this framework has been presented by numerous meta-analytic reviews investigating its explanatory power, e.g. Sheppard et al. (1988) and Albarracin et al. (2001). Despite this scholarly confirmation, the TRA has frequently been criticised for different reasons, though. Firstly, empirical findings indicate that attitudinal and normative variables may not always be completely independent of each other (Ryan, 1982, pp. 263-278). Rather, cognitive and normative evaluations exhibit a complex set of dependencies. In addition, it was found that the interview setting (e.g. different wordings for questions) can systematically foster a change in the hierarchy of individual's beliefs (Sutton, et al., 2003, p. 246; Armitage & Christian, 2003, p. 194). Secondly, referring to the abovementioned criticism on the aggregate expectancy-value structure, the operationalisation of primary beliefs in a composed attitude model sense is still subject of a controversial discussion. Again, it must be stressed that quantifying subjective beliefs in terms of probabilities is considered problematic from a methodological perspective (Ahtola, 1975, p. 52 ff.).

In consequence of the restrictive assumptions of this explanatory model, TRA has often been applied in modified and extended forms. One boundary condition consists of the presumption of a pure volitional control, where limited resources such as time, environmental circumstances or personal ability do not restrict the freedom of action. Thus, in order to explicitly address cases of incomplete volitional control, Ajzen proposed in (1985) an extension of TRA, referred to as the **Theory of Panned behaviour** (TPB). This integrative theoretical framework predicts behaviours by incorporating beliefs regarding the availability of relevant resources or pertaining opportunities. The complete path model is shown in Figure 3.3. Therein, the additional predictor *perceived behavioural control* is modelled as an exogenous construct that influences behaviour both directly and indirectly through intentions (Madden, et al., 1992, p. 4). It borrows basically from Bandura's hypothetical concept of 'self-efficacy', which reflects the self-percept of operative capabilities in human agency (Bandura, 1977, p. 191 ff.). In addition, Ajzen's definition of behavioural control encompasses perceived external constraints on behaviour in that this construct moderates the relationship between intention and behaviour. Hence, perceived behavioural control is regarded in a broader sense as "both a proxy measure of actual control and a measure of confidence in one's ability" (Armitage & Christian, 2003, p. 191).

Even though the TPB has proven to contribute significantly to the prediction of intention and behaviour (e.g. Armitage and Conner 2002, Conner and Sparks 1996; Rivis and Sheeran 2003), in an innovation adoption context perceived behavioural barriers can be disregarded for research economic reasons. As a rule, it is very difficult for consumers to accurately estimate behaviourally relevant resources and abilities. Nevertheless, this conceptual framework has received much attention in social psychology as a well-researched model for parsimoniously explaining behavioural intentions and actual behaviour in various application fields, including health, pro-environmental and travel behaviour (e.g. Glanz et al. 2008; Steg and Vlek 2008; Bamberg et al. 2003). In order to extend the applicability of the TPB to specific goals and investigational contexts, some researches have further improved the predictive efficiency of the model by adding a number of situational background factors to the system of hypotheses. For example, additional predictors such as 'knowledge' (Harakeh, et al., 2004), 'feelings of regret'

(Kaiser, 2006), 'moral sensitivity' (Buchan, 2005) and 'self-identity' (Smith, et al., 2008) have been developed so far. To sum up, the TPB is principally open for further extensions and modifications.

Consequently, in (1995a) Tayler and Todd establish a **Decomposed Theory of Planned Behavior** (DTPB). In order to consider possible crossover effects between the normative and attitudinal components, they extended the original model by decomposing exogenous belief structures into multidimensional belief constructs. The main objective for postulating this extended path model was to provide a more insightful and thus diagnostically more valuable explanation of consumer adoption behaviour in a wide variety of settings (Tayler & Todd, 1995b, p. 151). As the respective monolithic belief structures become more differentiated according to single influence factors that could be manipulated (e.g. through system design strategies), the DTPB appears to be more managerially relevant.

Drawing upon Roger's innovation characteristics, this decomposition approach suggests the second-order latent variables 'relative advantage', 'compatibility' and 'complexity' for particularising the underlying complex attitudinal belief structures. In this way, it takes into account that the cognitive component of attitude formation may not be organised into a single conceptual unit (Shimp & Kavas, 1984, p. 795-809). With respect to the aforementioned conceptual division of perceived behavioural control into internal and external behavioural constraints, the controllability belief structure is further decomposed into 'self-efficacy' and 'facilitating conditions'. Moreover, the subjective norm construct provides exemplarily the two dimensions 'peer influence' and 'superior's influence'. Here, the decomposition is based upon the divergence of views among relevant referent groups, such as peers, superiors and subordinates in organisational settings.

In the context of IT usage, the authors empirically found a comparatively high degree of explanatory power of the decomposed TPB (Tayler & Todd, 1995b, p. 168 ff.). Yet, they concede that in comparison to other competing behavioural models the DTPB is considerably less parsimonious by virtue of seven complementary second-order constructs. Generally, for making an appropriate model selection it is recommended to consider the relative trade-off between parsimony and contribution to knowledge (Mulaik, et al., 1989, pp. 430-445). Therefore, the value added by means of the increased explanatory power should at least compensate the added structural complexity. For the present investigational purposes, the decomposed version of TPB would be less valuable considering the complexity and the lack of specificity for explaining wearable technology acceptance. Consequently, it appears reasonable to draw rather on the original conceptual frameworks. In this context, several investigators strongly suggest to improve the predictive power of attitude theory (i.e. TRA and TPB, respectively) by "trading specificity for parsimony" (Bagozzi, 1992, p. 201), i.e. by integrating additional explanatory variables into the source models.

3.1.2.3 The Technology Acceptance Model and Competing Variants

The **Technology Acceptance Model** (TAM) originally introduced by Davis in (1980) has already been successfully applied to different adoption behaviours across a broad range of information technologies and user populations. Moreover, several meta-analytic reviews strongly support the theory's predictions in the Information Systems field, e.g. (Ma & Liu, 2004). Since this nomological framework relates to IT acceptance in organisational settings, primarily an extrinsically motivated system utilisation is central to the underlying causal-analytical

considerations. In this model, product characteristics represent external stimuli that evoke internal decision processes which ultimately manifest in overt computer usage behaviours. Basically, the TAM is an adaption of TRA specifically tailored to Information Systems research (Davis, et al., 1989, p. 983). An overview of the predictive model is given in Figure 3.5.

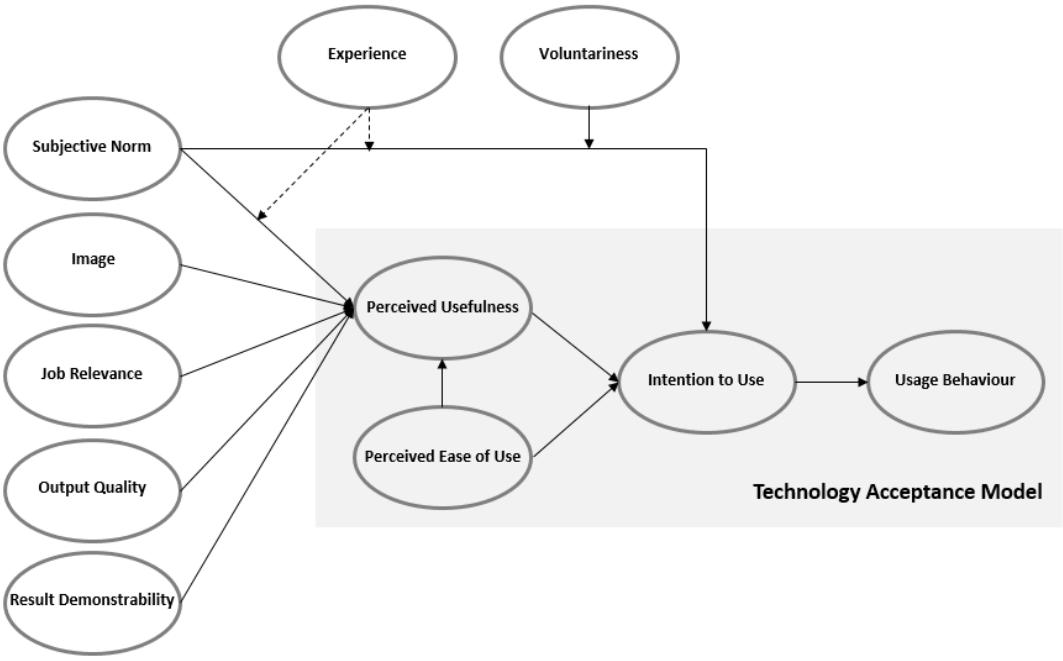

Figure 3.5: Path model of the TAM and its extension (Based on Venkatesh & Davis 2000, p. 188)

The TAM differs from its theoretical source model in that it explicitly excludes the normative component. Davis argues that his research setting focuses mainly on prototypes, so only a rudimentary social influence may be expected (Davis, 1985 p. 36 f.). Since this assumption likely applies to wearable technologies too, social norm was excluded from further analysis in the present study as well. Moreover, corresponding with the trichotomous view of attitude (see chapter 3.1.1) this originally formulated model posits affective, cognitive and both conceptually and structurally separated conative correlates of behaviour. Cognitive beliefs (or expectancies) are reflected through the two latent key constructs 'perceived usefulness' and 'perceived ease of use' as powerful and simultaneously parsimonious predictors of IT usage intention. Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1985 p. 26), whereas perceived ease of use is conceptualised as "the degree to which a person believes that using a particular system would be free of effort" (ibid.). Since both motivational drivers of IT usage intention are of a formative nature, they contribute to a greater epistemological and practical value as opposed to TPB – particularly, since they model relevant belief structures in a disaggregated way which allows for a comparison of the relative influence of different beliefs (Davis, 1985 p. 27). In regard to the 'ease of use' construct, it should be critically stated that before hands-on experience with IT systems usability perceptions follow more abstract, general product criteria in terms of cognitive heuristics (Venkatesh, et al., 1996 p. 453 f.). However, after direct experience (e.g. via small-scale usability tests), judgements of user-friendliness are rather based on more concrete, denotative system features. Such appraisals may be considered more ecologically valid.

Overall, contrarily to the TPB, the TAM's belief set of extrinsic motives in terms of both usefulness and usability dimensions readily generalises across different investigational situations that focus on the adoption of technological innovations. Both cognitive components are themselves predictable from measures of specific external variables, such as system features and system experience (Davis, 1985 p. 24 f.). Actually, system characteristics were among the first external stimuli found to predetermine usefulness and usability perceptions (Venkatesh, et al., 1996 p. 457).

Furthermore, the original conceptual model implies that the intention to use an IT system is a function of attitude in the sense of an overall affective reaction to system usage (Davis, 1985 p. 43). However, after conducting a post hoc data analysis, Davis et al. (1989, p. 999) found that the model only partially fit the empirical material. They proposed in (1989) a revised version of TAM. The most notable deviation is the lack of the attitude construct. The authors establish that empirical evidence indicates at best a partial mediation of the relationship between cognitive beliefs and usage intention through attitude. Davis et al. (ibid.) conclusively argue that in working environments IT usage intention is primarily induced by anticipated consequences on job performance – regardless of affective reactions. In other words, an employee may have a negative attitude towards a computer system, but still use it by reason of expected performance gains. On the other hand, mandatory adoption decisions can also be characterised as situations where social norms to use an ICT system overpower beliefs about expected effects (Linders, 2006). By empirically comparing eight prominent acceptance models in Information Systems research, Venkatesh et al. figured out that affective processes are only significant in such instances, where performance and effort expectancies are not anchored in the hypothesis system (2003, p. 455). The scholars therefore assume that in mandatory work settings any observed covariation between attitude and volitional intention is immanently spurious. Aside from that, the omission of attitude may provide valuable insights concerning the distinct influence of perceived ease of use and perceived usefulness on usage intentions (Venkatesh, 2000, p. 343). Given the assumption of a primarily cognition-based usage decision, much subsequent research on IT acceptance employing the revised TAM has yielded fairly adequate reliability and validity results in predicting future IT use, including Szajna (1996), Karahanna et al. (2006), Yi et al. (2006), as well as Saadé and Bahli (2005).

In sum, owing to its simplicity and specificity TAM qualifies as a well-suited and robust intention model within an organisational application context. In settings of non-voluntary IT employment this causal model can explain about 40% of variance in behavioural intentions and up to 30% of system usage (Venkatesh, 2000, p. 355; Meister & Compeau, 2002). Given the considered utilitarian motives represented by perceived usefulness and ease of use, praxeological recommendations for product policy may be derived: To the extent that these factors are behavioural correlates, they provide direction to system designers as to where efforts should be focused, since a developer has some degree of control over same (Tayler & Todd, 1995b, p. 145). However, the parsimony of TAM is simultaneously its major drawback. In particular, some investigators have challenged the model's ability to explain consumer adoption of technologies in a private consumption context (Chen & Mort, 2007, p. 356). By drawing on motivational theory, others claim that incorporating the hedonic, pleasure-oriented nature of IT system usage into the explanatory model would be more meaningful (Van der Heijden, 2004, p. 695 ff.; Bagozzi, et al., 1992). Yet, one of the most frequently cited and well explored aspects of system usage decisions is the social influence dimension including subjective norm, image and voluntariness. As a consequence, Venkatesh and Davis theorise in (2000) an extension of TAM by incorporating social influence as well as cognitive instrumental processes (i.e.

job relevance, output quality, and result demonstrability) into the underlying system of hypotheses. This integrated cause-and-effect model, subsequently referred to as TAM2, was repeatedly validated in both voluntary and mandatory settings. It outperforms the source model especially in volitional contexts and, therefore, also limits its range of possible applications (Hossain, 2014, p. 4).

Due to the multitude of specific needs in Information Systems research, the TAM has undergone substantial refinements and extensions since its publication. A growing body of research has tried to maximise the conceptual model's explanatory power by synthesising commensurable and complementary theories and concepts applying to the acceptance formation process in context-specific domains. In response to the increasingly fragmented landscape of theories attempting to tailor TAM to the respective investigational particularities, Venkatesh et al. formulated in (2003) a **Unified Theory of Acceptance and Use of Technology** (UTAUT). In the course of a critical review of several competing acceptance models (including TRA, TPB, TAM, the 'C-TAM-TPB' depicting a hybrid of TAM and TPB, see Taylor & Todd, 1995a, the 'Motivational Model' by Bagozzi et al., 1992, the 'Model of PC Utilization' developed by Thompson et al., 1991, the 'Social Cognitive Theory' according to Compeau and Higgins, 1995, and Roger's IDT), they identified four main exogenous drivers of behavioural IT usage tendencies: performance expectancy, effort expectancy and social influence are conceptualised as direct antecedents of intention, whereas facilitating conditions directly influence usage behaviour (Venkatesh, et al., 2003 p. 447). These crucial key constructs all have been distilled from the above theoretical bases by means of significance and unique explained variance. For instance, performance expectancy is, among others, based on the constructs perceived usefulness (Davis, 1985) and relative advantage (Rogers, 1983a), circumscribing "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh, et al., 2003 p. 447). Effort expectancy in turn originates mainly from perceived ease of use (Davis 1985) and the innovation characteristic of complexity (Rogers, 1983), capturing the degree of conceived ergonomics posed by a given technological system. The social influence construct, on the other hand, relies basically on attitude theory (i.e. TRA, TPB and C-TAM-TPB), referring to the subjectively anticipated expectations of relevant social groups. Eventually, facilitating conditions include perceived behavioural control (Ajzen, 1991) and thus describe "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh, et al., 2003 p. 453). In refinement of this nomological network, the intervening variables 'gender', 'age', 'experience' and 'voluntariness of use' were found to significantly moderate the intention and usage dependencies.

Even though the UTAUT has consistently shown strong predictive and explanatory utility, it is relatively seldom used in management practice, yet (Blagov & Bogolyubov, 2013, pp. 37-45). Rather, a large majority of contemporary research in the field of Information Systems draws upon the original base models TRA, TPB and TAM. However, in order to fit specific needs and to improve predictive or explanatory power, the original formulations have frequently been modified by extending the source models with domain-specific interacting constructs (Planing, 2014 p. 53). Table 3.1 provides an overview of relevant empirical analyses focussing on technological innovations in ubiquitous or mobile computing environments in a broader sense, which are akin to the research subject of the present study as regards content.

Research context	Author(s)	Theoretical Base	Validated Additional Constructs
Acceptance of health information technology	Ketikidis et al. 2012	TAM	Computer Anxiety, Social Norm
Consumer acceptance of mobile payment services	Schierz, et al., 2010	TAM	Individual Mobility, Perceived Compatibility, Social Norm
Explaining multi-channel consumer's channel-migration intention	Pookulangara, et al., 2011	TRA	Hedonic Beliefs
m-Payment Acceptance Model in Virtual Social Networks	Liébana-Cabanillas, et al., 2014	TAM	External Influences, Risk, Trust, Social Influences, Social Norm
Determinants Influencing the Diffusion of Mobile Internet	Alwahaishi & Snášel, 2013	UTAUT	Perceived Value, Perceived Playfulness, Attention Focus
User acceptance of media tablets	Yu, et al., 2015	TAM	Perceived Value, Perceived Enjoyment, Social Image, Perceived Risk, Personal Innovativeness, Experience
Analysis of users and non-users of smartphone applications	Verkasalo, et al., 2010	C-TAM-TPB	Technical Barriers, Perceived Enjoyment, Social Influence
Adoption of healthcare wearable devices	Li, et al., 2016	TAM	Perceived Privacy Risk, Information Sensitivity, Personal Innovativeness, Legislative Protection, Perceived Prestige, Perceived Informativeness, Functional Congruence
Explaining and predicting Facebook continuance participation	Al-Debei, et al., 2013	TPB	Perceived Value
The impact of use context on mobile services acceptance	Mallat, et al., 2009	TAM	Mobility, Compatibility
Smartwatch adoption	Chuah, et al., 2016	TAM	Visibility
Drivers of the Acceptance of Augmented Reality Smart Glasses	Rauschnabel, et al., 2016	TAM	Self-presentation, Social Norm, Brand Perception, Individual Difference Variables
The role of personality in individual awareness and intended adoption of Google Glass	Rauschnabel, et al., 2015a	TAM	Social Conformity, Individual Difference Variables
Acceptance Factors of Non-Users and Satisfaction Factors of Users of Tablet-PCs	Kim, et al., 2012	TAM	Playability, Cost Level, Complexity, Self-efficacy, Innovativeness

Research context	Author(s)	Theoretical Base	Validated Additional Constructs
Factors influencing the intention to use mobile payment	Kim, et al., 2010	TAM	Innovativeness, M-payment-knowledge, Mobility, Reachability, Convenience, Compatibility
Social Motivation To Use Gamification	Hamari & Koivisto, 2013	TPB	Network Exposure, Recognition Reciprocal Benefit, Continued Use Intention
Adoption of WAP-enabled mobile phones	Teo & Pok, 2003	TPB	Risk, Compatibility, Image
Drivers of mobile commerce	Wu & Wang, 2005	TAM	Perceived Risk, Cost, Compatibility
Information technology acceptance by individual professionals	Yi, et al., 2006	C-TAM-TPB	Personal Innovativeness, Result Demonstrability
Consumer acceptance of internet of things technology	Gao, et al., 2014	TAM	Trust, Social Influence, Perceived Enjoyment, Perceived Behavioural Control
TAM in a ubiquitous computing environment: The case of wireless LAN	Yoon & Kim, 2007	TAM	Perceived Convenience
Driver's Intention to Use Smartphone-Car Connectivity	Park, et al., 2013	UTAUT	Technographics, Mobile Literacy, Prior Similar Experience
Information Security Behaviour	Zhang, et al., 2009	TPB	Perceived Security Protection Mechanism
Acceptance of Remote Services	Wünderlich, 2009	C-TAM-TPB	Trustworthiness, Role Clarity, Role Ability, Trust in Technology, Intrinsic Motivation
Determinants of accepting wireless mobile data services	Lu, et al., 2008	TAM	Mobile Trust, Personal Innovativeness, Facilitating Conditions, Social Influences, Wireless Mobile Data Services Technology
Intentions to use mobile services	Nysveen, et al., 2005	C-TAM-TPB	Perceived Expressiveness, Perceived Enjoyment, Normative Pressure

Table 3.1: Relevant contemporary research in the area of IT innovations acceptance

It appears that research with technology focus is primarily based on TAM, since no tailored belief dimensions have to be elicited as is regularly the case in attitude research (i.e. TRA and TPB). Nevertheless, none of the publications so far examine causative acceptance factors specifically in wearable computing environments. Instead, the available extensions inevitably reduce the universality of the original behavioural models as discussed above.

Summing up the chapter, basic behaviour-oriented acceptance concepts and theories in the field of Information Systems have been introduced. Relating these behavioural base models to the present research context, it seems reasonable to rely on TAM as an empirically evident theoretical frame of reference for conceptualising intermediary psychographic processes in an IT adoption context. However, as stated before the propositions included in this conceptual source model are fairly generic in nature, disregarding the specificities of the actual research questions under scrutiny. In order to contribute to the scientific body of knowledge in Information Systems research as well as to enhance the predictive performance and explanatory power of TAM in the case of wearable computing, a dedicated cause-effect model has to be synthesised. This framework should build on and integrate relevant principles and insights in technology acceptance literature under the ontological assumption of critical realism (cf. chapter 4).

3.2 Technology Acceptance from a Perceived Risk Perspective

From a managerial viewpoint, it is very important to account for consumer's resistance to innovation as one of the major causes for market failure (Hosseini, et al., 2016). In an ICT adoption context, especially information security risks influence resistance behaviour (Tsiakis, 2012 p. 1265). The following sections therefore critically examine risk perceptions in general and IT security risk perceptions in particular. In order to relate these concepts to the study subject, the chapter takes a consumer's perspective. To this end, the role of risk perceptions within the adoption process is outlined in the first instance. Then the structure of subjective risk is delineated.

3.2.1 On the Behavioural Relevance of Perceived Risk

Suffering from the inherent pro-innovation bias, which is based on the premise that all innovations are good without exception and that they always improve existing product substitutes (see chapter 3.1.1.), the vast amount of academic literature on innovation diffusion has prevalently restricted itself to the adoption and diffusion perspectives (Ram, 1987 p. 208; Rogers, 2010 p. 100). This leads to a systematic neglect of possible rejections or discontinuances of innovations. However, innovations impose a change in existing behavioural patterns or belief systems, whilst the process of change resistance is a normal consumer response, annually manifesting in a high failure rate of new products and services in the economy (Claudy, et al., 2014, p. 528). By reflecting this research gap, marketing approaches largely promote reasons for innovation adoption and, hence, primarily attempt to stimulate adoption decisions rather than reducing consumers' initial innovation resistance. However, any marketing investments in later decision process stages are wasted if consumers reject innovations prior to evaluate their benefits (Talke & Heidenreich, 2014, p. 895). Therefore, marketing instruments should also focus on potential inhibitors to adoption that result in resistance.

While some scholars regard innovation resistance as a generic, personality-related predisposition, others equate this phenomenon with an aversive attitudinal outcome following an unfavourable product evaluation (Talke & Heidenreich, 2014, p. 896). The former explanation for the focal decision anomaly relates to an adopter-specific propensity to resist changes, caused by a multifaceted personality trait including dimensions such as routine seeking, emotional reaction to change, short-term focus, and cognitive rigidity (Oreg, 2003, p. 680). Interestingly,

in an Information Systems context, the willingness to change - as definitional antipode of the propensity to innovation resistance - is reflected by the individual's personal innovativeness in terms of an adopter-related predisposition (Agarwal, et al., 1998 p. 206; Sheth, 1981 p. 274).

On the contrary, the latter form of consumer resistance evolves from innovation-specific factors. Sheth argues in (1981, p. 275) that the most suitable theoretical constructs in understanding contra-adoption cognitions are, firstly, *habit towards existing practices or behaviours* and, secondly, *perceived risks associated with innovation adoption*. The first psychological barrier arises as soon as an individual perceives inconsistencies with past experiences, since humans intrinsically strive for consistency and status quo maintenance. However, as per definition, disruptive innovations call for a higher degree of adaption of habitual problem-solving behaviours on consumer side (see chapter 3.1.1). Consequently, the compatibility of a new technology with existing practices can be neglected from an epistemological point of view.

The second adoption barrier refers to the subjectively felt uncertainty about an innovation's possible negative performance outcomes. Correspondingly, Mitchell points out that *perceived risk* is a relatively powerful construct for explaining consumer behaviour, as individuals tend to avoid mistakes rather than to maximise utility in purchasing (1999, p. 163). The author demarks this concept from the notion of uncertainty by ascribing a known probability component to the former term (1999, p. 166). Nonetheless, the 'known' probability element may also describe a subjective probability having no relation to the actual intersubjective reality. This specification of perceived risk relies on the two-component model of risk, which captures the risk perception by multiplying the subjectively perceived probability of occurrence of a salient adverse behavioural consequence with the relative cost or severity of that potential loss or exposure (Bettman, 1973, p. 189). Again, ordinally scaling the subjective probability component and multiplicatively linking it to the germane severity component leads to comparable methodological problems as stated in the case of expectancy-value structures in attitude measurement (see chapter 3.1.2.1). Cunningham accordingly establishes that such a risk conceptualisation may not contribute to a deeper understanding of consumer behaviour, since humans do not think in probabilities (1967, p. 83; Gardner, et al., 1998, p. 5). Therefore, the subjective probability of the occurrence of adverse outcomes will be disregarded in the course of the present study. Instead, in the following the perceived risk concept is understood in terms of a subjectively quantifiable measure of *anticipated* negative outcomes of innovation adoption.

Risk research in the context of TAM and related theories has empirically proved both direct and indirect attitude-mediated influences of IT risk perceptions on behavioural intention. In contrast, other studies found no moderating effect of the focal construct. For instance, Featherman and Pavlou showed a direct negative impact of perceived risk on the perceived usefulness and adoption intention (2003, p. 456). On the contrary, Yang and Wu conceptualised the risk construct as moderating the causal dependency structures of purchase intention (2009, p. 371): In such instances where consumers perceive a greater risk of purchasing an innovation, the relationship between consumer's purchase intention and its antecedents becomes significantly weaker. However – as will be shown hereafter – the incorporation of risk as a moderator variable into exploratory models of attitude is methodically quite difficult insofar that this construct correlates with other central acceptance factors. This might lead to an erroneous interpretation of statistical results.

Choi and Geisterfeld examined in (2004, p. 823 ff.) the online-shopping behaviour of American and Korean consumers by defining perceived security as an important behavioural attitude towards e-shopping. This conceptualisation of risk, however, seems questionable since consumer apprehension has variously been proven to be a clearly discriminable determinant of attitude. A great number of studies in acceptance research found that it are rather cost-benefit considerations that play an important role in purchase-decision making (Sweeney, et al., 1999 p. 79; Kim, et al., 2007). Numerous frameworks on consumers' decision-making thus regard perceived value (in the sense of a cost-benefit ratio or cognitive attitude) as a dichotomous net-valence resulting from favourable and unfavourable product properties. Expected utility theory – in turn originated from modern microeconomic theory – provides a theoretical underpinning for these value concept (Snoj, et al., 2004, p. 157).

Zeithaml describes customer value perception as a trade-off between total benefits perceived ('get' component) and total sacrifices ('give' component). The author thereby takes both positive and negative valences in purchase decisions into account (1988, p. 13). Former interpretations of the benefit and sacrifice components mainly centre on perceived quality and monetary price, ignoring the multidimensional nature of cognitive decision-making (Kim, et al., 2007 p. 113). Especially perceived sacrifices have been shown to consist of diverse non-monetary costs including time, effort and psychological costs for purchase and consumption. Sweeney et al. hence emphasise the relevance of perceived risk to perceived value, as specifically in the case of durable goods consumers usually consider longer-term implications of product ownership (1999, p. 80). Against the backdrop that such a structural path explication evidently leads to a greater explanatory power, the present thesis follows this recommendation and distinguishes between cost and benefit dimensions in terms of aversive and positive attitudinal beliefs at behavioural level. Based on empirical evidence (Featherman, et al., 2003 p. 460), furthermore, a negative direct relationship between perceived risk and behavioural intent to adopt a new technology is presumed.

3.2.2 On the Dimensionality of Perceived Risk

On the supposition that consumer behaviour could be regarded as an instance of risk taking (Bauer, 1960, pp. 389-398), past social psychology research has exploratively identified five major categories of perceived risk including performance, financial, social, psychological and physical risk facets. Notably, the relevance of each category in cognitive risk processing differs between specific situations and adoption domains (Mitchell, 1999 p. 180 ff.). In an e-services research context, the latter risk category has meanwhile been transferred into a privacy-related risk dimension, since utilisation of ICT poses a direct threat to personal data rather than to physical safety (Featherman, et al., 2003 p. 454). Moreover, researchers in the field of Information Systems increasingly maintain that in a technology acceptance context, especially the appraisal of potential security incidents is of prime importance. On that account, perceived risk has frequently been construed as two conceptually separate, unidimensional constructs of privacy and information security perceptions (Liebermann & Stashevsky, 2002, p. 292 f.).

Prior research studies on IT adoption confirmed IT security perceptions (understood as an inverse measure of perceived risk) to be significantly associated with online transaction behaviour (Vijayasarathy & Jones, 2000, p. 200; Cunningham, et al., 2005, pp. 357-372; Tsai & Yeh, 2010, p. 4059; Godwin, 2001, p. 171). Yet, drawing from e-commerce empiricism, even though security is a key concern in online B2C environments, this central concept has not received much academic attention (Im, et al., 2008 p. 1). With the advent of modern pervasive and

ubiquitous computing systems, perceived IT security hence may provide a renewed impetus to acceptance research, raising the following questions (Diamantopoulos, et al., 2001 p. 271; Rossiter, 2002 p. 305):

- What conceptual working definition is appropriate for this phenomenon with respect to its content and scope,
- what dimensionality does this conceptualisation include, and
- how should this latent variable be integrated into the sought overall system of statements, so as to attain a holistic understanding of the acceptance formation towards innovative technologies.

First of all, marketing practitioners should keep in mind that risk is rather a subjective perception than an objective characteristic of a product (Fain & Roberts, 1997, p. 53). Even though it is feasible to objectively measure the degree of security inherent to a given technology environment, the congruence of this measure with the exact consumer perceptions remains unclear (Chellappa & Pavlou, 2002, p. 359). Given that subjective perspectives may differ from the scientific ones (what could be shown in an analysis of novice and expert judgements during technology usage, see Schenk, et al., 1998, p. 9 ff.), it are ultimately *personal anticipations* of security threats that influence trust in exchange environments. Subjective security beliefs from a user-centred perspective refer, however, to theoretical mechanisms built upon concrete technological solutions. Because perceived security is hence influenced by implicitly perceptible measures, the antecedents of risk perceptions should describe tangible technical or legal aspects (Chellappa & Pavlou, 2002, p. 361; Flavián & Guinalíu, 2006, p. 604). In practical terms, by accurately identifying these theoretical obstacles, more efficient marketing strategies will become available that may stimulate demand. Finally, understanding crucial adoption inhibitors may enable providers to employ appropriate means for reducing consumers' risk levels (Liebermann & Stashevsky, 2002, p. 292).

Still, existing theoretical definitions of subjectively felt IT security risks in Information Systems and other relevant literature are throughout positioned in B2C contexts and thus primarily focusing on on-line transactions in open communication networks. For instance, Salisbury et al. define perceived security as "the extent to which one believes that the Web is secure for transmitting sensitive information" (2001, p. 167), whereas Hartono et al. theorise this construct to reflect "the degree to which the online buyer believes that conducting an online transaction on the seller's website is safe in a manner consistent with the buyer's confident expectations" (2014, p. 12). On the contrary, Chellappa et al. understand security perceptions more comprehensively as "the subjective probability with which consumers believe that their personal information will not be viewed, stored or manipulated during transit or storage by inappropriate parties, in a manner consistent with their confident expectations" (2002, p. 360).

Recent research, though, shows that consumers' information security concerns regarding mobile ecosystems considerably deviate from their attitudes towards traditional computing systems (Chin, et al., 2012, p. 1). According to the studies, these deviations can mostly be attributed to differences in system usage contexts. This applies all the more for wearable technologies since the wearables' sensor capabilities together with their continuous access and ubiquitous presence open up a new threat landscape. Particularly, the potentially constant storage, access and transmission of private, sensitive or even critical information in sometimes unsecure network environments may result in a conglomerate of familiar and unfamiliar types of data at an unprecedented rate,

raising unique security implications (Lee, et al., 2015). Therefore, a taxonomy of security threats based on how information is affected appears to be applicable.

In IT security literature, the international standard ISO/IEC 27002:2013 is considered to be the most comprehensive best practice framework for information security management (Saint-Germain, 2005, p. 60; Qingxiong & Pearson, 2005, p. 578; Topi & Tucker, 2014, p. 59). Evolved out of the second part of the British Standard BS 7799 and superseding its previous versions 'ISO 17799' and 'ISO 27002:2005' (Chang & Ho, 2006, p. 348; BSI Group, 2013), this conceptual framework for modelling information security principles and practices characterises *information* as an asset that has value to interested parties and thus exerts a vital impact on operational efficiency and competence. Consequently, the goal of information security as understood by this authoritative security norm is to protect socio-technical systems from the ever-increasing spectrum of potential threats including i.a. technical accidents and legal issues, such as personal data processing. These threats might result from various sources of vulnerabilities (e.g. personnel, applications, communications, and environment software) which were abbreviated in ISO 27000 series to the categories of confidentiality, integrity and availability (Chang & Ho, 2006, p. 347). Following this abstract categorisation of IT security objectives, Lindström suggests to structure security requirements in wearable computing environments according to the 'higher requirement levels' as encompassed by the CIA triad (Lindström, 2007, p. 4). By drawing on EU Directives (Directive 95/46/EC) and other Council decisions regarding data security and wearables, the author explicitly states that "when processing, storing or transferring personal data, the confidentiality and integrity of the data must be secured" (ibid.). In addition, ad-hoc networks and unreliable access points pose further security problems including the availability of network access (Lindström & Hanken, 2013, p. 104). Particularly in view of the increasing reliance on pervasive computing systems in various aspects of daily life, information availability becomes even more apparent – all the more considering the limited battery life-time of mobile devices. Ultimately, this information security issue constitutes a point of vulnerability as well (Martin, et al., 2004, p. 309). Given that wearables are always-on and continuously data gathering devices, Blum (2015) stresses that security executives should pay extra attention to preserve information confidentiality, integrity and availability for wearable displays. Considering the above definitions from Information Systems literature and adapting them to a wearable computing context, the following working definition may adequately capture the essence of perceived security towards the focal object of investigation:

The degree to which users belief that relevant information services will be timely available and personal data will not be viewed, stored, and manipulated during processing, storage or transfer by inappropriate parties in a manner consistent with their confident expectations.

This definition implicitly suggests that security is conceived as an abstract higher-order factor, consisting of several constitutive dimensions. Contrary to this conceptualisation, available empirical studies in the Information Systems area has mostly ignored the concept's multifaceted nature and operationalised measures that tend to capture only one dimension of perceived security (Hartono, et al., 2014, p. 11). For instance, Salisbury et al. (2001, p. 173 ff.) incorporated the singular construct 'Perceived Web Security' into the TAM and demonstrated by this means a strong correlation between on-line purchase intentions and security-related perceptions. Furthermore, in an e-commerce context Liao and Cheung could increase predictive efficiency of their acceptance model by integrating a

unidimensional security construct (2002, p. 293). Certainly, these studies shed light on the role of perceived security in various communication environments. However, the exclusion of underlying first-order factors prevents from important insights concerning the priority of the respective formative paths influencing the overall security perception, especially since different operational contexts pose a different need for security requirements (Lindström, 2007, p. 4). In practice, analysis of the relative importance of salient risk beliefs should be included in managerial resource allocation decisions.

The present study therefore seeks to refine the security-related adoption barrier in order to comprehensively understand consumer behaviour in wearable technology markets. According to Hartono et al. (2014, p. 12), the earliest and most widely employed predictors in currently sparse literature on security perception issues are reflected by the classic CIA triad framework. Former research has added various other security objectives over the years, such as non-repudiation, authenticity, accountability, and privacy (Solms & Niekerk, 2013, p. 98; ISRMC, LLC, 2009; Flavián & Guinalíu, 2006, p. 603). Nonetheless, the traditional three core principles still remain overarching goals in information security management (Merkow & Breithaupt, 2014, p. 21). Given that recent studies suggest to consider relevance, non-redundancy, and completeness as dimension inclusion criteria (Hartono, et al., 2014, p. 13), for the sake of parsimony only the three traditional cornerstones of security are considered in the following. In view of the relevance of the perceived risk phenomena as a central adoption inhibitor in wearable technology markets, the next subchapter is devoted to latent variables exogenous to this theoretical construct in order to broaden understanding of consumers' resistance behaviour towards technical innovations.

3.3 On the Antecedents of Cognitive Beliefs

The following sections seek to determine the causes of both risk and benefit expectations in order to augment the understanding of the latent mechanisms underlying an ICT adoption decision.

3.3.1 Perceived Risk as a Correlate of Trust

In many disciplines of behavioural sciences and economics, trust has been a key construct (Suh & Han, 2002, p. 249; Wünderlich, 2009, p. 75). This resulted in a plurality of definitions across different research areas including marketing (e.g. Fisher et al. 2010; Hong 2015), economic (e.g. Dasgupta 1990; Goodwin 1996) and management literature (e.g. Balasubramanian et al. 2003; Jeffries & Reed 2000). Despite the conceptually divergent perspectives on trust, the following cross-disciplinary definition is well-accepted among most scholars: "Trust is a psychological state comprising the intention to accept vulnerability based on positive expectations of the intentions or behaviours of another" (Rousseau, et al., 1998, p. 395). By implication, trust is a party's willingness to rely on the assumption that another party concerned will not behave harmful or in an opportunistic manner under conditions of dependence and risk (Currall, et al., 1995). In exchange environments, consumer trust is considered to be crucial regarding the individual decision-making behaviour and, therefore, represents also a key success factor in purchase situations (Pavlou, 2003, p. 70).

Given that the relevance of perceived risk in B2C electronic commerce is well-established – not least due to inherent consumer's apprehensions associated with online transactions via open e-infrastructures with unknown

Internet vendors – the increasing importance of online environments has heightened interest in trust as a significant influencing factor of individual risk perceptions (Gefen, et al., 2008, p. 278; Pavlou, 2003, p. 79). Various empirical studies on trusting beliefs in the online context indicate that this latent variable represents a key predictor for approach and avoidance behaviour in Internet commerce. For instance, Jarvenpaa et al. (1999) found that a trusting stance towards a merchant organisation helps consumers to overcome their reluctance to purchase online, what generally emphasises the need of trust in online activities. Furthermore, by conducting a confirmatory analysis, Pavlou (2003, p. 91) showed empirically that risk perceptions and trust jointly influence the intention to perform transactions via electronic channels. This implies that uncertainty reduction is an integral component in acceptance behaviour. In line with this school of thought, Gefen et al. (2003a, p. 74) integrated trust into TAM and proved thereby that heightened levels of consumer trust (in terms of specific beliefs about an e-vendor) ultimately result in an increase of the likelihood of customer retention in an electronic commerce context.

In most studies trust was found to influence behavioural intent indirectly through perceived costs, i.e. risk perceptions. Still, the interwoven nexus between trust and risk has given rise to several, sometimes quasi contradictory interpretations on how perceptions of trust and risk inter-relate. Lim (2003, p.217) provides a detailed overview of the different conceptual models of the trust-risk nexus. Five main views dominate the understanding of the trust-risk connection (see Figure 3.6): In the first instance (a), risk is considered to moderate the effect of trust on consumer's willingness to respond positively. A second paradigm theorises that trusting behaviour prerequisites at least an equilibrium between trust and risk perceptions, where the level of trust must outweigh the felt hazardousness of an action (b). A third view suppose that the relationship between perceived risk and trust is recursive, representing a unidimensional effect (c). Thereby, most scholars regard risk perception as a dependent, and trust as an exogenous variable (e.g. Cheung and Lee, 2001). Finally, other researches assume that the relation between trust and risk perceptions is non-recursive (d) (e.g. Mitchell, 1999). Nonetheless, following the most commonly modelled paths in acceptance research (Huijts, et al., 2012, p. 528), the present study assumes that trust is a direct antecedent of perceived risk (c) and thus affects conative attitude indirectly through risk perceptions.

Case	Description	Reference
(a)	Perceived risk ↓ Trust → Willingness to buy	Steward (1999)
(b)	Trust → Perceived risk → Trusting behaviour	Kim and Prabhakar (2000)
(c)	Trust → Perceived risk	Cheung and Lee (2001)
(d)	Trust ↔ Perceived risk	Mitchell (1999)

Figure 3.6: Trust-risk relationships (Based on Lim 2003, p. 217)

Until recently, the marketing literature has narrowly focused on transactional byer-seller interconnections, stressing the relevance of sales agents as prime objects of trust in relationship marketing (Bart, et al., 2005, p. 134). Unlike interpersonal trust in dyadic consumer-marketer interactions, in an ICT adoption context the object of trust

refers to technical aspects, such as a Web site, the Internet or a technology. In the Information Systems field, consumer trust and trustworthiness make thus reference to a global belief that the technological product will perform the required functions and that actors who are responsible for the technology will fulfil their obligations as understood by the buyer (Gefen, 2004, p. 264). However, most trust-related studies in the field examine primarily vendor- or institution-based effects of trust as a measure of interpersonal or person-to-firm relations, e.g. Gefen (2004), Mathieson et al. (2001) as well as Pavlou and Gefen (2004).

In trust-related Information Systems research this theoretical view is reflected in the widely employed conceptualisation of consumer trust as a tripartite construct, consisting of the sub-dimensions 'ability', 'benevolence', and 'integrity', which comprehensively shape the conceived trustworthiness of a trustee (Mayer, et al., 1995, p. 715). However, just recently the central role of *consumer trust in specific technologies* has been recognised in Information Systems research. In today's complex computing environments, where individuals increasingly develop greater dependence upon ICT systems, trusting beliefs involve not only human actors, but more and more also IT artefacts (Wang & Benbasat, 2008, p. 268; Vance, et al., 2008, p. 74). Lippert and Forman (2006, p. 271) thus allege that by virtue of anticipated aversive long-term consequences (e.g. long learning curves and additionally accruing operating costs), any technology adoption bears uncertainty from a user perspective. Given that technological innovations might not feature the expected capabilities or functionality for accomplishing an envisaged task, trustors largely lack control over consequences of IT usage as in the case of interpersonal exchange relationships. Accordingly, drawing upon prior research on interpersonal trust, McKnight et al. (2011, p. 12:5) understand technology trust as a second-order, object-specific belief set based on the respective system's functionality (related to 'ability'), helpfulness (related to 'benevolence') and predictability (related to 'integrity').

In a mobile payment context, Luarn and Juo found in (2010, p. 889) a significant interaction term between trust in an emerging technology itself and the actual usage behaviour. In supporting this finding, Thatcher et al. (2011, p. 66) empirically demonstrated that trust in a specific IT artefact substantially affects postadoption exploration of the system. Vance et al. (2008, p. 74 ff.) investigated trust within a mobile commerce scenario and developed a framework for understanding the system quality characteristics that build or diminish consumer's willingness to trust. They clearly emphasise the role of trust in the diffusion of an innovation (ibid.). Hence, from a commercial point of view, deepening the extant understanding of the recently arisen trust concept is expected to lead to valuable insights concerning consumer's adoption patterns. In-depth knowledge of the effects of trust thus may help to better understand the pace and nature of product growth in innovative markets (McKnight, et al., 2002, p. 334).

3.3.2 Perceived Usefulness as a Correlate of Perceived Pervasiveness

As outlined in chapter 3.1.2.3, TAM is considered to be a partial model that provides solely a middle range theory. Due to its parsimony, it is generically applicable to traditional technology adoption and acceptance contexts. Nonetheless, when technological paradigms change, this boundary condition of the current research stream hinders scholarly investigation from specifically analysing the distinguishing characteristics inherent to an altering class of technologies (Bagozzi, 2007, p. 245). In the Information Systems field scholars therefore call for further research on technology acceptance. The base model should be augmented by means of a coherent integration of additional generic or universal predictors that are particularly relevant to the prevailing object under scrutiny

(Bagozzi, 2007 p. 244; Sheng, et al., 2014 p. 462; Schierz, et al., 2010 p. 210). Such an introduction of further exogenous variables should deepen the original TAM conceptualisation by explaining its central concepts of cognition-based beliefs (i.e. perceived usefulness and perceived ease of use) to gain a better understanding of consumer acceptance in different domains.

With respect to the present object under investigation, especially the shift towards ubiquitous computing becomes apparent. This paradigm shift distinguishes pervasive or ubiquitous information systems from classical computing environments insofar that seamless mobility, context-awareness as well as a sense of 'unobtrusiveness' turn into key characteristics of the emerging genre of computing (Perich, et al., 2004, p. 630). As per definition, the pervasive ICT system's scope is substantially broader than those of traditional desktop PCs. Pervasive systems dynamically apply to varying settings without being stationary or requiring explicit control of the user (Lyytinen, et al., 2004, p. 64; Birnbaum, 1997, p. 41). Therefore, in pursuing to predict ubiquitous or pervasive information systems adoption, the classical nomological net of technology adoption falls too short. In order to overcome this shortcoming, the TAM was deepened for the present study by introducing a further hypothetical construct. This latent variable should be able to explain a sufficient amount of variance in utility perceptions, specifically in a ubiquitous computing context.

By correlating pervasive information systems with technology acceptance theories, Karaiskos (2009) initially conceptualised and validated a measure of *perceived pervasiveness* in ubiquitous computing environments. Drawing on the well-researched behavioural, normative and control beliefs in acceptance research (see chapter 3.1.2.2), the author incorporated a new pervasiveness perspective into the original TAM, so as to reflect the inherent characteristics of pervasive computing. In his introductory work he conceptualised and factor-analytically validated pervasiveness, which is depicted in Figure 3.7. This exogenous construct is based on the theoretical assumption that pervasiveness is an abstract formed, superordinate concept that particularly emphasises on the amalgamation of information appliances and human's living conditions (Karaiskos, 2009, p. 80 ff.; Xu, et al., 2007, p. 772). From a causal-analytical viewpoint, pervasiveness acts as an antecedent of the endogenous cognitive and affective acceptance factors that are commonly considered to be behaviourally-relevant in Information Systems and marketing literature (Karaiskos, 2009, p. 150). Substantially, three self-sustained dimensions synthesise the construct's conceptual scope and thus denote its dimensionality. These three constituting dimensions are framed as follows (Karaiskos, 2009, p. 81 ff.):

- **Ubiquity**. This pervasiveness dimension relates to the continuous accessibility to a pervasive information system's resources without spatial or temporal boundaries.
- **Unobtrusiveness**. The unobtrusiveness dimension refers to the invisibility of the pervasive information appliance in terms of a non-distracting and non-disrupting, but simultaneously proactive operational support of the user.
- **Context awareness**. This dimension describes the dynamical adaptability of a system to contextual cues. This includes the capture of context-relevant information through sensory capabilities as well as the management of these data in real-time.

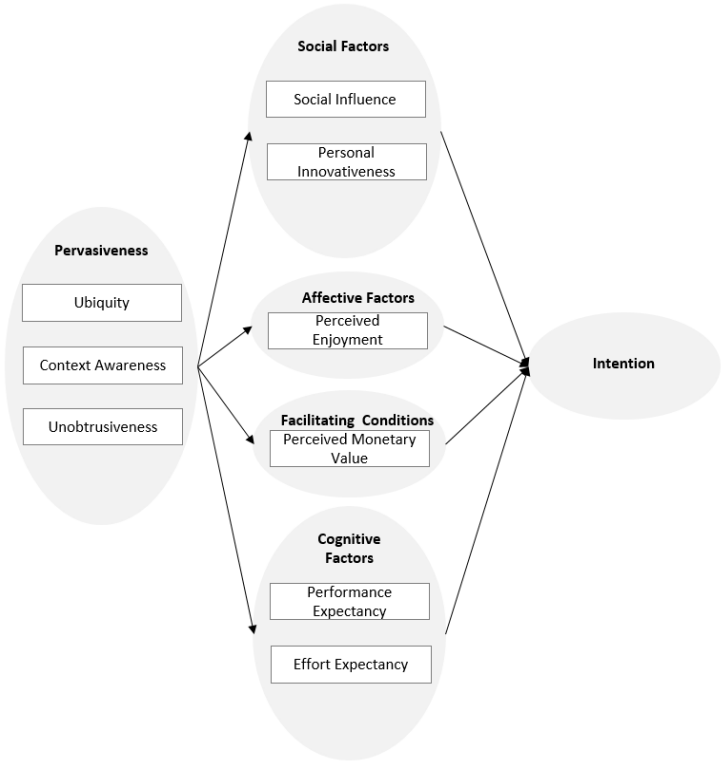

Figure 3.7: The perceived pervasiveness construct related to the behavioural intention to use a pervasive information system (Based on Karaiskos 2009, p. 153)

Karaiskos provides both theoretical and empirical support for the overall effectiveness of the perceived pervasiveness concept as a multifaceted variable in regard of its reliability, construct and nomological validity (2009, p. 174). Building on this understanding, Koondhar et al. (2015) propose a conceptual framework for measuring the acceptance of pervasive learning in a non-western culture. Within their causal model, the pervasiveness domain maps inherent particularities of the emerged Information Systems class. Accordingly, pervasiveness is theorised to subsume context awareness, unobtrusiveness and ubiquity perceptions and to directly covary with the 'perceived usefulness' and 'perceived ease of use' belief systems (Koondhar, et al., 2015, p. 101). However, this research is still in progress, which is why quantitative assessments of their theoretical model are not yet available. This research gap clearly incentivises further research on the internal and nomological structure of the focal independent variable through alternative theoretical lenses.

3.4 Chapter Conclusions

This chapter aimed at providing a theoretical foundation for wearable computing acceptance. Due to the absence of explanatory models that are tailored towards measuring wearable computing acceptance, different well-established behavioural theories and concepts were scrutinised. These frameworks are of particular importance to the study subject since they all approach innovation acceptance behaviour from different angles. In order to meet the main research objectives, the research topic was first located within the broader context of innovation diffusion and then within the narrower frame of Information Systems and technology acceptance research. Existing adoption

models were critically evaluated and an overview was given of contemporary empirical investigations which explicitly apply these models and which focus on comparable technological innovations. The literature review revealed that the TAM has already been successfully employed across various research settings and that this theoretical framework is best suited to explain and predict acceptance behaviour in an information systems context.

Still, the generic cause-effect relationships provided by the TAM fall too short in explaining the adoption of emerging technologies such as wearable computing. To further augment this base model with new, subject-relevant concepts that may improve predictive and explanatory power, *perceived security risk* as a salient belief was discussed from a consumer perspective and put in relation to technology adoption theories. To reach a more comprehensive understanding of what influences the reluctance to use an upcoming technology, perceived risk was conceptualised as a multidimensional construct, which clearly stands in contrast to the usual specification of IT security risk in innovation adoption literature. Finally, another recent topic in Information Systems research, the *perceived pervasiveness* of a technology, has been introduced. This cognitive belief appears particularly promising in the given study context since it captures the specific features of the novel wearable computing paradigm. In order to identify further concepts that are implicated in the individual intention formation and, thus, may serve as a starting point for model development, in the following the qualitative approach of this research is discussed in detail.

4 Qualitative Interview Study

This chapter deals with the exploratory part of the research programme at hand. It is organised as follows: Firstly, it outlines the philosophical approach towards the research problem. Secondly, aligned with the research questions under investigation, it discusses appropriate methods and procedures for collecting and analysing qualitative data. Finally, based on the proposed research design and the obtained empirical material, it draws interim conclusions on the market success factors of wearable computing. These findings may provide a well-founded starting point for hypotheses formulation.

4.1 Qualitative Research Methodology

Constitutive to the practical part of the qualitative study, this section aims at circumscribing the methodological base of the actual research. The rationale for choosing a mixed-methodological approach that combines qualitative and quantitative data, is given. Also, information is provided about how a qualitative study ought to be carried out in general and how inductively collected data can be evaluated adequately.

4.1.1 Epistemological and Methodological Considerations

At present, academic research in the area of ubiquitous and wearable computing acceptance is still relatively scarce (Shin, 2010 p. 169; Chuah, et al., 2016). This makes an explorative research phase indispensable, so as to motivate and legitimise research on interpersonal success factors of wearable computing adoption. In particular, the explorative insights are expected to highlight the need for developing a new, multi-factor measurement model of effectuation and causation from a consumer viewpoint. In a broader sense, a multi-methodological approach has been employed for the purpose of the present research work which links conceptual, qualitative, and quantitative research studies through *sequential triangulation*.

From a meta-theoretical perspective, prior to the definition of a methodological strategy it first has to be determined if the research problem is primarily qualitative or quantitative in essence (Morse, 1991, p. 120). Qualitative research is usually of a diagnostic exploratory nature, questioning search and simultaneously representing a search for questions (de Ruyter & Scholl, 1998, p. 8). This research strategy finds its roots from the field of sociology, which marks “a science which attempts the interpretive understanding of social action in order to arrive at a causal explanation of its course and effects” (Weber, 1947, p. 88).

	Qualitative Methods	**Quantitative Methods**
Research goals	Discovery of new ideas; preliminary understanding of ideas and objects	Validation of facts, estimates, relationships and predictions
Type of research	Exploratory designs	Descriptive and causal designs

	Qualitative Methods	Quantitative Methods
Strategies of inquiry	Narrative research, case study, Grounded Theory, Phenomenology, Ethnography	Experimental and non-experimental (e.g. surveys)
Type of questions	Open-ended, unstructured, probing	Mostly structured
Time of execution	Relatively short time frame	Generally, significantly longer time frame
Representativeness	Small samples; limited to sampled individuals	Large samples; typically good representation of population
Type of analysis	Debriefing, subjective, content analysis, interpretive	Statistical, descriptive, and causal predictions
Generalisability	Limited; only preliminary insights and understanding	Normally very good, inferences about facts and relationships

Table 4.1: Main distinguishing characteristics between qualitative and quantitative research (Based on Creswell et al., 2018, p. 11 ff. and Hair et al. 2003, p. 212)

Under the premise of a socially constructed reality, qualitative research emphasises discovery over confirmation by reconstructing subjective theories (Holliday, 2008, p. 6; Newman & Benz, 1998, p. xviii). This method of inquiry differs from quantitative research in that it typically adopts analytic-inductive processes of reasoning. Qualitative studies aim at theory building, rather than pursuing the deductive tradition in terms of theory testing. They seek to put forth a richness of detailed data on a small number of individuals (Hyde, 2000, p. 84; Deshpande, 1983, p. 105). The main distinguishing characteristics between qualitative and quantitative research can be taken from Table 4.1.

The central study's assumption that attitudinal and behavioural dimensions of consumer decision-making play a crucial role in wearable market's growth already finds confirmation in diffusion and Information Systems literature (see previous chapter). Still, this research issue lacks more detailed empirical-inductive research in order to arrive at a sufficiently sound and meaningful theoretical foundation for hypothesis generating. Therefore, a preliminary qualitative approach has been chosen in the course of this thesis. Drawing upon an extensive review of relevant academic literature in the field of innovation diffusion, Information Systems and attitude research, the objectives of the qualitative inquiry have been set as follows: (1) Formulate the research problem more precisely regarding the scope of the empirical setting, (2) exploring subjective beliefs and perceptions current and prospective users have towards wearable computing and (3) establish a proper theoretical basis for the development of a coherent system of hypotheses by gaining deeper insights into relevant individual and situational circumstances that affect the belief formation towards wearables.

More specifically, building upon the preceding literature review and seeking convergence to the main research questions and theoretical findings, the exploratory study aims at clarifying the following areas in order to serve as a prelude to subsequent quantitative research processes:

- Characteristics and causalities of the wearable technology market

- Drivers of wearable computing adoption
- Inhibitors of wearable computing adoption

However, up to now, in marketing science and Information Systems research a mono-methodological employment of standardised quantitative models clearly predominates (Planing, 2014). Yet, the historically developed over-reliance on deductive processes in the context of social scientific studies has encountered multiple criticism. For example, Deshpane (1983, p. 106) complains that marketing scholars tend to apply exclusively quantitative methodological processes even on concepts that are still immature. In addition, Wells (1993, p. 490 ff.) criticises that the comprehensiveness in theorising would be insufficient, that statistical significance would confer real causality and, furthermore, that there is a dominance of one-shot studies. Especially the latter criticism has increasingly become addressed in consumer research over the last decades (Johnson, et al., 2007, p. 112).

Given our limited access to the world through perceptual and theoretical lenses, the post-positivist paradigm (in a Kantian sense) ontologically assumes that there is an objective, causally efficacious but only imperfectly conceivable reality. Following this view, a mixed-methodological approach appears most promising, emphasising the importance of multiple observations and methods with their different types of inherent deficiencies and unique strengths (Guba & Lincoln, 1994, p. 100; Mingers, et al., 2013, p. 795). This relatively new research paradigm acknowledges that the convergence of findings from two or more methods fallible in their own diverse ways "enhances our belief that the results are valid and not a methodological artefact" (Bouchard, 1976, p. 268). The complementary combination of several methodological perspectives may compensate the specific weaknesses and blind spots of each single method and hence reduce the overall error of measurement.

More precisely, in light of the study's superior purpose of transferable and generalizable explanations and predictions of consumer behaviour, critical realism comes more to fore (Mingers, et al., 2013, p. 800). This post-positivist ontology assumes that subjectivity is inherent to all concepts in social sciences, since they are ultimately human constructions (Bryman & Bell, 2015, p. 62). As a consequence, claims about reality have to be critically examined to the greatest possible extent in order to advance apprehension of reality (Guba & Lincoln, 1994, p. 110). Following this reasoning and given that qualitative approaches may compensate for deficiencies in quantitative research, critical realism espouses the combination of both methodologies. Methodologically, this philosophical tradition thus implies a mixed-method research design. It grounds the simultaneous use of qualitative and quantitative methods in the same research endeavour and, consequently, shapes the logic of inference in the course of the research process. In view of its particular suitability for Information Systems research (Zachariadis, et al., 2013, p. 856), the present study holds the meta-theoretical stance of critical realism.

One of the most common functions of mixed methods is triangulation. This research strategy suggests that the combination of data or methods in the study of the same social phenomenon results in superior explanations (Bryman, 2006, p. 108; Johnson, et al., 2007, p. 115). According to Denzin (1978, p. 14) who coined this theoretical term, there are basically three possible outcomes that may arise from triangulation strategy: convergence, inconsistency, and contradiction. Whichever outcome predominates, the researcher attains more corroborating evidence for constructing profound propositions about a given phenomenon (Mathison, 1988, p. 15).

Thus, for validation purposes a multi-strategy research was employed in this study. The methodological triangulation posed a multi-stage research process in which data from both the conceptual and the qualitative stage built the foundation for subsequent quantitative research. The findings from the initial exploratory approach were matched against the concepts that evolved from the review of the pertaining theoretical and empirical findings in literature that relate to the adoption of new information technologies (such as utility and risk perceptions). The resulting categories of beliefs towards wearable computing acceptance finally constituted the main content of the Wearable TAM that could be further tested quantitatively.

4.1.2 Qualitative Approach to Data Collection

Overall, the aim of the qualitative study is to identify concepts that are involved in the individual belief formation towards the adoption of wearable computing. However, this research phase is not intended to report on quality criteria such as significance values or potential correlations between those concepts. Rather, in order to elaborate and extend existing theory, it pursues to holistically conceptualise the individual decision to adopt wearable technologies. The findings of this study constitute a building block for the development of the explanative model and, as such, guide the proceeding of this research.

According to Mack et al. (2005, p. 2), the most common qualitative methods are: participant observation, in-depth interviews and focus groups. As the present study aims at eliciting *latent* attitudinal factors, direct observations may not be viable. Moreover, focus groups have the fundamental drawback that their results are a direct function of group dynamics, potentially leading to biased findings (Churchill & Iacobucci, 2010, p. 67). In-depth interviews, on the contrary, enable to bring out the 'complex stock of knowledge' (Flick, 2009, p. 156) persons have about the topic under study. Since personal one-to-one interviews are very well suited for eliciting salient behavioural, normative and efficacy beliefs (Montano, et al., 2008, p. 80), this qualitative research method matches the research aims stated.

Previous qualitative research has developed various methodological alternatives to collect verbal data. In broad terms, the different interview methods alternate between the goal of either producing openness or producing structure (Flick, 2009, p. 211). Therefore, the choice of a method should be based on the given research objectives as anchor points, which intrinsically pose the need for exploration or rather explanation. Recalling the research goals of this study, the central aim is to develop a comprehensive understanding of which socio-psychological factors influence the decision-making towards the acceptance of wearable computing. Thus, the interviews should be oriented towards a thematic direction. At the same time, this study seeks to reveal *latent* beliefs towards wearable computing adoption in mass markets as a new field, i.e. making implicit knowledge more explicit. In view of this persisting research gap, the need for a supplementary explorative function to acquire more background knowledge about the study topic becomes acute. Consequently, a semi-structured interview type appears appropriate for the present purposes.

A specific form of semi-structured interviews is the expert interview, which neither refers to highly open nor to rigid structured question-answer schemes (Flick, 2009, p. 165). With regard to thematic directedness, interviews are structured by an *ex-ante* devised interview guide, which essentially reflects its underlying conceptual framework. This gives the interviewer the flexibility to vary or interpose questions, so that more elaborate

responses may arise, which potentially lead to a disclosure of implicit knowledge or hidden facets of human behaviour (Qu & Dumay, 2011, p. 246). On the other hand, the objectives of research are conveyed consistently by the interview schedule, directing the conversion in a systematic way (Lienhard & Preuss, 2014, p. 74).

The target group of expert interviews comprises informants possessing a specific in-practice knowledge within a professional sphere of activity (Schmitt, 2014, p. 33; Flick, 2009, p. 166). Considering that qualitative research seeks transferability rather than generalisability of results, an adequate sample size is "one that adequately answers the research question" (Marshall, 1996, p. 523). An iterative, nonprobability approach to sampling is thus required, where data collection is a cybernetic process that is controlled by the emerging theory (Glaser & Strauss, 2009, p. 45; Ritchie, et al., 2013, p. 115). This means that further samples have to be selected iteratively for refining emerging categories from initially analysed data. Typically, the population of interest is recruited on the basis of the potential contribution to the body of knowledge its members have in a certain social system. Hence, in qualitative research the sample is usually derived purposefully rather than randomly, focussing primarily on the *information-richness* of each case (Onwuegbuzie & Leech, 2007, p. 242; Patton, 1990, p. 181). Consequently, significant information redundancy marks the point of theoretical saturation, when no further insights or perspectives are forthcoming from ongoing data collection and the conceptual categories or theories of relevance are fully explicated (Morse, 2001, p. 66).

In view of the classical quality requirements (i.e. validity and reliability) in scientific research, qualitative methods have frequently been criticised from quantitative research community because they are often regarded as failing the standard criteria of scientific adequacy or rigor (Sandelowski, 1986, p. 27). Responding to this critique, various qualitative methodologists have constructed new typologies of validity, transferring some basic aspects from quantitative tradition to the field of qualitative inquiry (Seale, 1999, p. 465). These evaluation criteria make up a huge array of new terms for the trustworthiness or credibility of qualitative research projects, redefining concepts of validity and reliability in inductive contexts including authenticity, dependability, confirmability, goodness, verisimilitude, fittingness and plausibility (Creswell & Miller, 2000, p. 124; Flick, 2009, p. 396; Golafshani, 2003, p. 604). Yet, most inductive research methods adhere to a relative freedom of structure and rigour. Their very nature suggests that the quality of qualitative studies should be assessed by its own paradigm's concepts (Stenbacka, 2001, p. 551). As qualitative research emphasises on meaning rather than on measurement, Stenbacka (ibid.) argues that the traditional validity concept in its quantitative sense addressing the question of whether "the intended object of measurement actually is measured" has no relevance in inductive approaches. Accordingly, in qualitative research validity refers primarily to the fact "that constructs are closely aligned to their real-life context" (de Ruyter & Scholl, 1998, p. 13). Therefore, results become significant only in relation to the informant's everyday reality. Insofar, de Ruyter and Scholl contend that qualitative inquiry provides the possibility of 'ecological validity' as opposed to construct validity or internal validity (2003, p. 13; Wünderlich, 2009, p. 96).

External validity in the sense of a quality criteria for quantitative research refers to the validity structure of generalised inferences (Johnson, 1997, p. 289). However, generalisability is usually not the prime purpose of qualitative research, what is evident from the fact that qualitative methods seldom aim at selecting random samples as the most appropriate sampling technique to generalise from a sample to a population. Qualitative methodologists focus more on particularities than on universalistic findings. Thus, Yin translates in (1989, p. 21) statistical generalisation

into analytical generalisation, where the investigator's goal is to expand and generalise theories and not to numerate frequencies. According to Stenbacka (2001, p. 552), an analytical understanding can be attained by elevating the empirical material to a general level.

In quantitative research, reliability refers to how consistently a technique reproduces results from measuring a specific concept repetitively (Rao & Perry, 2003, p. 241). Therefore, as reliability by definition concerns measurement, Stenbacka (2001, p. 552) postulates that the issue of repetitive correctness has relatively little value in research settings dominated by the inductive demand for *conditional subjectivity*. Other scholars argue that qualitative research does not primarily demand reproducibility, but much more a systematic operation at the level of the research design (i.e. methods and techniques) linking the empirical material to the central theoretical models or concepts (de Ruyter & Scholl, 1998, p. 13).

Accordingly, Flick (2009, p. 397) gives rise to the question of whether qualitative research should generally look for strategies of quality assessment rather than on inter-methodological evaluation criteria. Drawing upon the recommendations of qualitative methodologists in literature, best-practices in qualitative study should be integrated into the preparatory design of a research project, so as to shape and direct the research during its development and to establish the trustworthiness of its results (Creswell & Miller, 2000, p. 124; Morse, et al., 2002, p. 18). Thus, to achieve validity and reliability in the above sense, this study employs eight quality verification mechanisms adopted from literature in the field (Stenbacka, 2001; de Ruyter and Scholl, 1998; Rao and Perry, 2003; Healy and Perry, 2000; Wünderlich, 2009), which are summarised in Table 4.2.

	Employed Tactics	Objective
Ecological Validity	• All expert interviews were performed in the informant's own environment (de Ruyter, et al., 1998 p. 13; Wünderlich, 2009 p. 98), i.e. they were interviewed at their own place of work. • The informants were given the opportunity to speak openly according to their knowledge structures (Stenbacka, 2001, p. 552). Consequently, closed-ended questions were not asked. • The interviews were performed in a flexible manner including specific analytical in-depth probing where appropriate (de Ruyter & Scholl, 1998, p. 13).	Ensuring valid perceptions and beliefs aligned to the informant's real-life context
External Validity	• The informants were strategically well-chosen rather than statistically drawn, as they are heavily involved in innovative wearable computing issues and, thus, assumingly more competent in the field for the sake of particular "information-richness" (Stenbacka, 2001, p. 555). To avoid personal bias in the choice of respondents, in three cases the snowballing technique was used, see chapter 4.2.1.	Ensuring credibility and generalisability of results in respect to theory

	• To ensure a cross-section of opinions, professionals with different perspectives on wearable technologies were selected (Rao & Perry, 2003, p. 241), cf. chapter 4.2.1. • The results of the analysis of the expert interviews (i.e. the emerged categories) were related to relevant Information Systems literature to be intersubjectively comprehensible and to ensure theoretical consistency of empirical interpretations (Creswell & Miller, 2000, p. 127; Bryant & Charmaz, 2010, p. 19).	
Reliability	• The interview guide was built upon extant theoretical frameworks and concepts in innovation adoption literature (cf. chapter 3), seeking to meet the analytical goals coherently (de Ruyter & Scholl, 1998, p. 13; Healy & Perry, 2000, p. 122). • The structured process for writing and interpreting data was documented in detail by means of an in-depth description of the employed study design in chapter 4.2 and a detailed matrix of emerged coding categories (de Ruyter & Scholl, 1998, p. 13; Rao & Perry, 2003, p. 241).	Ensuring confirmability, transparency and traceability of the original research design

Table 4.2: Employed verification mechanisms to achieve validity in a qualitative sense

4.1.3 Qualitative Content Analysis

Qualitative data analysis aims at transforming collected textual material into meaningful findings (Patton, 2002, p. 275). According to Robson (2009, p. 456), there are up to now no clear and commonly agreed conventions for analysis of qualitative data. Nevertheless, several approaches to a systematic content analysis exist, which can be broadly categorised into three methodologies: **conventional**, **directed**, and **summative analysis** (Hsieh & Shannon, 2005, p. 1278). Conventional content analysis deals with the description of a phenomenon on which academic literature and theories are limited. By contrast, directed content analysis pursues to complement existing theory or prior research that is deemed to be incomplete. Finally, summative content analysis aims at discovering underlying meanings of expressions by analysing the appearance of a particular word or content in the qualitative data.

Recalling the objectives of the explorative research phase, this thesis ought to employ a conventional content analysis. In this context, Mayring (2000) has developed a procedural model for qualitative content analysis (see Figure 4.1), which hallmarks an "[…] approach of empirical, methodological controlled analysis of texts within their context of communication, following content analytical rules and step by step models, without rash quantification". Basically, it is an iterative as well as reductive process. It systematically categorises manifest and latent content in a rule-bound way by employing at least partially inductively generated categories (i.e. derived from the data) that are internally homogeneous and externally heterogeneous by nature (Forman & Damschroder, 2008, p. 40; Mayring, 2000). It should be noticed here that qualitative content analysis should always be theory-

guided. This means that *technical ambiguity* of qualitatively oriented research imposes *theoretical stringency* in order to be compensated (Kohlbacher, 2005). Therefore, the theme of the categories to be formulated must be defined previously to attain a criterion for the selection process in line-by-line category development (Mayring, 2015, p. 374).

In a first step, following the objectives of the qualitative research, the material is successively reduced by omitting less relevant passages that transport no or only little content (first reduction). Subsequently, similar paraphrases are clustered (second reduction). This technique is commonly called **summarizing content analysis**, aiming at establishing an adequate abstraction level by reducing the material from one abstraction level to the next (Mayring, 2015, p. 374; Flick, 2009, p. 325). Afterwards, based on the research questions and aims, relevant passages are marked and the emerging aspects of text interpretation are put into categories line by line, which are diligently founded and revised within feedback loops. The first time textual material fitting the category definition is detected, a code or category has to be constructed with a label as near as possible to the text (Mayring, 2015). The next time a passage fitting the category definition is detected it has to be checked whether it is conceptually subsumed by the previous constructed code or requires a new code formulation. This technique is generally known as open coding, seeking to express data in the form of concepts that substantially describe the phenomenon under study (Flick, 2009, p. 307).

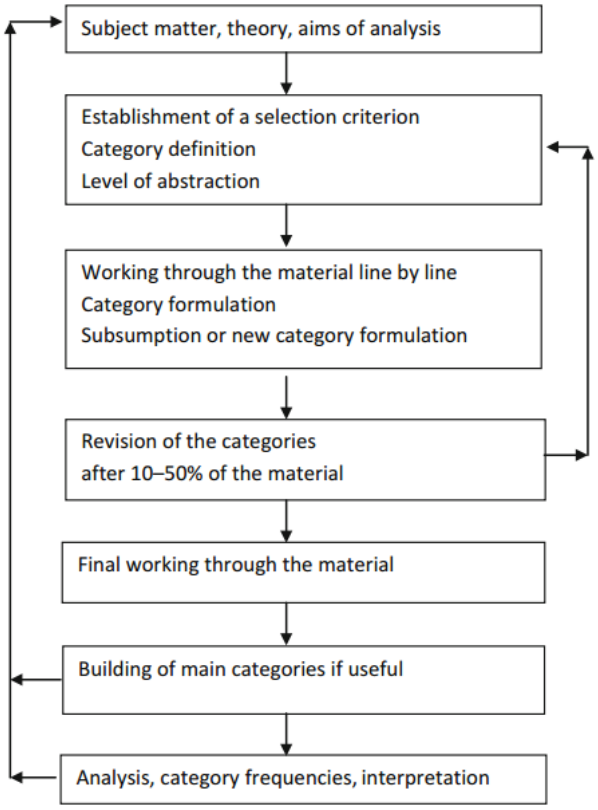

Figure 4.1: The process of inductive category development (Mayring 2015, p. 375)

Following grounded theory principles (Strauss & Corbin, 1998), in open coding codes or 'concepts' are formulated and linked to the analytical units of meaning, which classify expressions such as single words or short sequences of words. According to Flick (2009, p. 309) labelling codes can either be borrowed from literature (constructed

codes) or rephrasing parts of the source text (in-vivo codes). Thereupon, codes are categorised by grouping them around the theoretically relevant phenomena found in the material. The resulting categories are again attached to codes, which are now more abstract than those applied in the first step. The next step, commonly referred to as 'axial coding', refers to the elaboration of the relationships and dependability among the identified codes and categories resulting from open coding (Strauss & Corbin, 1998, p. 127). Essentially, the structures of relations between codes and categories are clarified by examining which code or category serves as a cause of the phenomenon and which category or code serves as a consequence of the phenomenon. Thus, axial coding is basically a process of systematically relating subcategories to more abstract, logical concept categories, supported by continuous comparison between categories and additional data. For instance, the subcategory 'Privacy' was condensed into the superordinate concept of 'IT security aspects'. Finally, selective coding aims at eliciting one core concept or phenomenon from which a substantive theory can be developed (Flick, 2009, p. 312). The central concept or phenomenon is systematically related to the fractured categories developed so far, whereby their interrelationships become validated. The content-analytical procedure ends at that point, where theoretical saturation has been reached, i.e. where further codes or categories no longer provide new knowledge (ibid.).

4.2 Design and Conduction of the Qualitative Study

This section describes how the interviews for the exploratory study were designed and administered. The conducted qualitative data analysis of the interview transcripts is discussed in detail. Thereupon, the inductive findings are presented.

4.2.1 Empirical Setting

As outlined above, the present exploratory research aims to provide an insight and understanding of attitude formation in wearable computing markets at a holistic level. Hence, a purposive theoretical sampling procedure was chosen to recruit particular informative respondents. Glaser and Holton (2004) define theoretical sampling as "the process of data collection for generating theory whereby the analyst jointly collects, codes, and analyses his data and decides which data to collect next and where to find them, in order to develop his theory as it emerges. This process of data collection is controlled by the emerging theory, whether substantive or formal". Thus, the decision on where to sample next was made in concert with the emerging codes and categories.

Theoretical sampling involves the purposeful selection of informants at least in the early stages of research (Coyne, 1997, p. 625). In this context, Sandelowski (1995, p. 181) remarks that there are essentially three variation strategies in purposive sampling: demographic, phenomenal, and theoretical variation. Demographic variation refers to a kind of maximum variation in purposeful sampling where variation is sought on general socio-demographic characteristics. The second kind of variation strategy represents a variation on the target phenomenon under study, what is also labelled as selective or criterion sampling (1995, p. 182). Theoretical variation, finally, refers to theoretically derived variations discerned in the data.

The objective of the present sample selection was to attain a sufficient sample heterogeneity in terms of maximal diversity of proficient interview participants. Accordingly, sampling was directed by the pursuit of including a

range of variations of the phenomenon under study (i.e. intention formation towards wearables). To generate rich information, the respondents' knowledge background was differentiated according to the criteria 'application focus', 'application area, and 'device type'. These criteria are assumed to ensure that participants are sufficiently interested, knowledgeable, and that they have much behavioural experience and are often exposed to latest information about the research object as suggested by Vannette (2015). As a consequence, laggards where not considered in the course of the explorative study. Rather, sample units with different perspectives on wearable computing (especially from industry and educational sector), with different levels of personal experience and with experiences of different types of wearables (especially smartwatches and smart glasses) were selected. Table 4.3 gives an overview over the main characteristics of the interviewees including their affiliation and professional position. In sum, the sampling decision was based on the aim of permeating the field and its structure in maximal depth (Flick, 2009 p. 123).

Interviewee	Company	Area	Role	Device Type	Focus
I1	Manufacturer in the automotive industry	Mobile Solutions	Manager	Smart Glasses and Smartwatches	Application researcher
I2	Engineering consulting office	City and traffic planning, mechanical and civil engineering, logistics	Director	Smart Glasses	Application researcher
I3	University of Applied Sciences	Research areas include knowledge management, enterprise social media and mobile business	Scientific coordinator at a technology transfer centre	Smart Clothes and Smartwatches	Application researcher
I4	University	Research institute focused on engineering science, division "Intelligent Production and Logistics Systems"	Research associate	Smart Glasses	Application researcher
I5	System house	Information technology	Senior system administrator	Smartwatch	User
I6	Public educational institution	Education	Technical service and IT administration	Smartwatch, Activity Tracker	User

Interviewee	Company	Area	Role	Device Type	Focus
I7	University of Applied Sciences	Lectures on innovation management	Professor	Smartwatches and Smart glasses	Application researcher

Table 4.3: Characteristics of the study interviewees

Overall, three academics from different research institutions participating in various wearable technology projects and four professionals from different companies within the Information Technology sector were interviewed. All interviewees were particularly involved in diverse wearable computing issues. They were thus expected to have a higher level of affinity towards wearables. As a consequence, the interviewees could provide more elaborate beliefs concerning the social and individual-level causal mechanisms involved in the adoption of wearable technologies. Besides the criteria of theoretical purpose and theoretical relevance, the sampling procedure was not controlled by any further selection criteria such as gender, age or social status.

The exploratory study was conducted in fall of 2015. All interviews were performed in German as the native language of the interviewees. Notably, in German language there is no authoritative term or definition available for wearable technologies, which is why the most common English word 'wearables' has been adopted without translation. The inquiries were carried out as semi-structured, open-ended interviews based on an interview guideline, and took between half an hour and one hour. Three out of the seven interviews were performed face-to-face, whilst the other four were telephone interviews, what allowed for wider geographical access. All participants were assured of confidentiality and anonymity. The telephone interview partners granted permission to tape-record the conversations, whereas the face-to-face interviewees agreed on taking notes during the interviews and on transcribing the communication. In terms of the general empirical setting, each interview was conducted at the subject's place of work, resembling 'real-world' conditions in favour of ecological validity.

Based on the theoretical findings from literature review, the interview guideline comprises a small set of carefully worded questions, aiming at exploring the general perceptions of wearable technologies as well as the central success factors of inter-individual acceptance. Structuring of the guideline and designing of the interviews included the categorisation of the predefined questions into groups as well as a standardised communication in approaching the sample units via email. Principally, certain questions could be omitted during the interviews, e.g. contingent upon the respondent's background and answers obtained. The open-endedness of the standardised questions allowed the respondents to contribute as much detailed information as possible. At the same time, the semi-structured approach allowed the investigator to ask probes as follow-up questions where appropriate. A probing question such as "tell me more about that" or "what did you learn" is an active listening technique to encourage informants to expand on an initial response and, thereby, potentially reveals aspects unknown to the author at the time of interview guide development (King & Horrocks, 2010, p. 40).

Within the introduction phase of the interview, the author made a short self-introduction and informed the interview partners of the general nature and purpose of the research in advance. According to Flick, it is crucial to create attention and a good atmosphere in early stages of an interview (2009, p. 172). Moreover, as recommended by Robson (2009, p. 279) it was explained to the participants why they were selected as interviewees and that they

could withdraw at any time from the interview. To comply with the ethical standards of scientific research, the interviewees were also asked for consent to conduct the interview. Furthermore, in order to arrive at a common understanding of the topic under study, the investigator briefly explained what exactly she meant by 'wearable technologies' and named some examples.

Subsequent to the introduction phase, the respondents were asked to convey their assessment of the current developments in wearable computing markets. Hereby, special focus was placed on a free discussion following the 'funnel' approach as suggested in (Morgan, 1996, p. 143). In funnel approach, the interview commences with fairly general questions and then proceeds to a variable set of more specific issues, progressively narrowing the topic area. This strategy is assumed to be most effective in constructing an inquiry or discourses (Roller, 2015). Therefore, after having assessed both the personal significance (e.g. what role wearables play for their companies and what devices are utilised for what purposes) and the perceived contemporary market situation of wearables, the interviewees discussed rather specific topics concerning the challenges, benefits and barriers to the usage of wearable technologies. Drawing on a quantitative social study on the advantages of wearable computing (see Brauer, et al., 2013), one additional item aimed at encouraging the interviewees to further elaborate on the benefits of wearable technology usage by naming specific utility dimensions (i.e. 'support of health and fitness', 'enhancement of personal abilities', 'boost of self-confidence', 'more control of personal life', and 'enhancement of social relationships'). In addition, to narrow the scope of the empirical setting, the professionals were asked what kind of wearables they consider most important for their stakeholders, e.g. smartwatches, smart glasses, or smart clothes. This way, the technologies that may be relevant for the quantitative study could be elicited. Afterwards, by addressing potential behavioural and societal changes that disruptive wearable technologies might engender, confronting questions were raised to stimulate further debate and reflection on the subject. Finally, the respondents were given the opportunity to discuss further topic-related issues outside the matters raised so far. Figure 4.2 shows the phase model of the developed interview design. The complete questionnaire can be found in Appendix A.1 of this thesis.

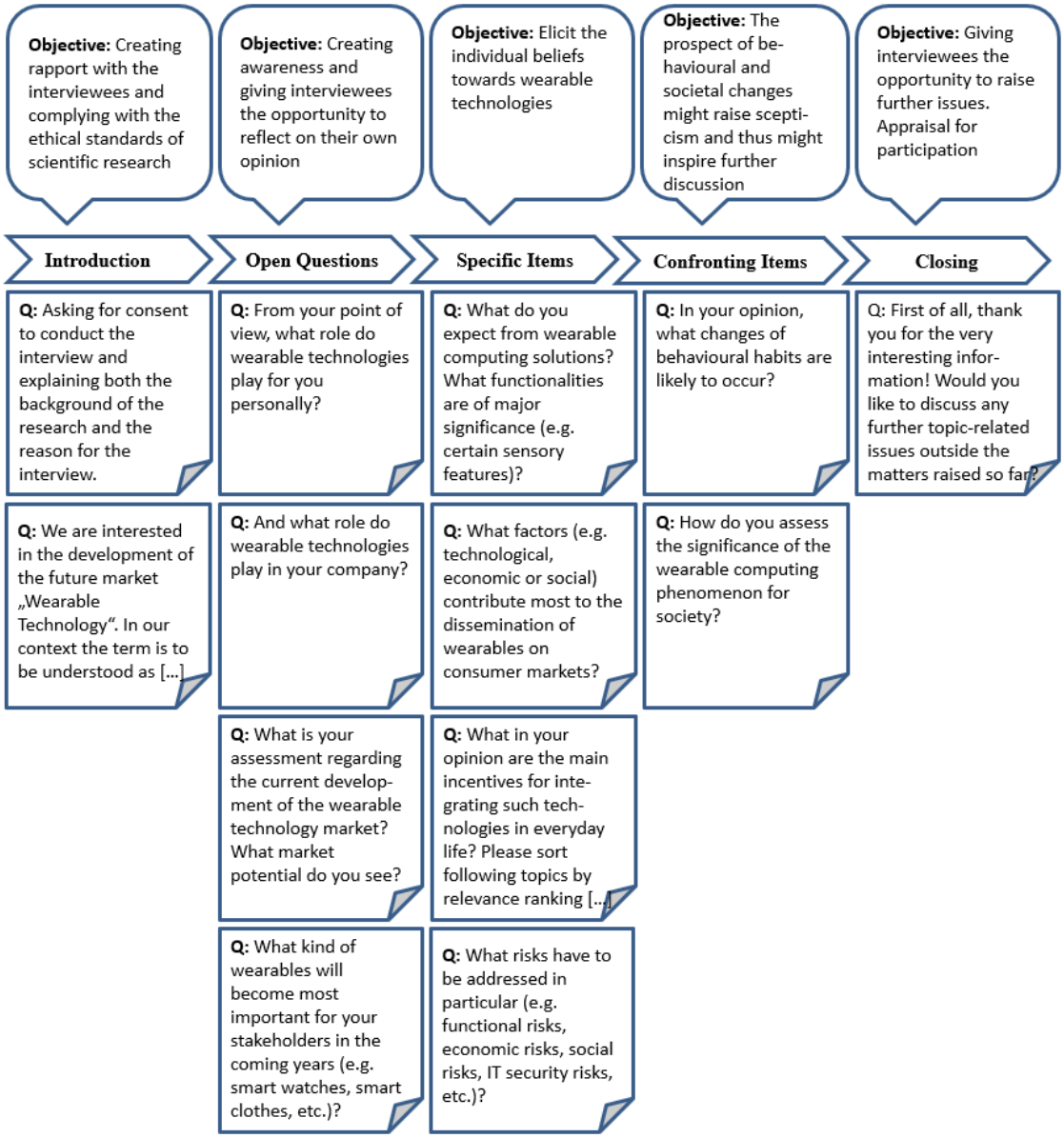

Figure 4.2: Phase model of the qualitative interview

As a theoretical sampling procedure was chosen for this study, data collection was controlled by the emerging codes and categories. Hence, the author simultaneously collected, coded and analysed the material, attempting to 'saturate' the relevant concepts and categories. In order to widen the contacts, in three cases the **snowballing** technique was used, whereby the interviewees were asked to suggest other informants. After interviewing the seventh subject, the point of informational redundancy had evidently been reached, since no new categories emerged from the data. Consequently, the need for further interviews ceased since no further findings were expected to contribute to the conceptual and theoretical understanding of the subject matter. Therefore, no further interviews were conducted.

4.2.2 Category development

Following the inductive category development process described by Mayring (2015, p. 375), to establish an appropriate level of abstraction, data analysis started with a material reduction procedure in terms of a summarising content analysis. This procedure had already been accomplished during the transcription process as a means of representing data verbatim. Since the substantive content of the expert interviews is most relevant for the present study, nonverbal aspects such as paralinguistic characteristics and prosodic components were neglected. In line with Bruce (1992, p. 145), who holds that "transcription system should be easy to write, easy to read, easy to learn, and easy to search", all interviews were transcribed in German standard orthography, disregarding deviations of pronunciation. The collected source material was condensed by discarding those chunks of data that intrinsically do not relate to wearable technology usage. Thus, the introduction phase together with some other off-topic conversations had been fully omitted in order to extract the essential contents for a comprehensive overview of the base material (Mayring, 2015, p. 373). Translated versions of all transcripts can be found in Appendix A.

After an initial familiarisation with the transcribed versions of the audiotapes and field notes, the process of data interpretation commenced by highlighting relevant parts of the text with regard to wearable technology acceptance. Subsequently, in-vivo codes were constructed from each marked meaning unit of analysis supported by the text (e.g. via single words, sentences, or paragraphs). Afterwards, these codes had been transferred into constructed codes in English, thereby being gradually abstracted into higher order concepts or categories in the course of an iterative process of constant revision (Corbin & Strauss, 1990, p. 420). Thus, codes with different wording that are nonetheless found to pertain to the same phenomenon were summarised into generic codes or categories. Table 4.4 exemplifies the data analysing process. In sum, 68 codes emerged from the analytical process, which constituted the basis for the further content analysis.

Transcript	**In-vivo Code**	**Constructed Code**
With regard to smartwatches, the developments in end consumer markets continue to look uncertain, as their added value isn't clearly visible. In addition, wearables are still higher-priced products and are thus rather perceived as prestige objects.	Added Value	Relative Advantage
	Higher-priced	Pricing Structure
	Prestige Object	Status-Consciousness

Table 4.4: Selected example of the open coding procedure

In a second step, axial and selective coding was employed to elaborate the hierarchical network of superior and inferior categories. To further conceptualise the properties of attitude formation in wearable technology markets, constructed codes and subcategories of similar content were aggregated into a coherent, overarching concept. For instance, the codes 'Status-consciousness' and 'Openness to Experience' were clustered into one logical content unit, as all these concepts include personality-related elements relating to behaviourally-relevant traits. Thus, a more abstract, higher-level category was developed with regard to the substantial meaning of the cluster of codes. Such superior categories were either one of the codes inferred from the text that readily represents the category in semantic terms or, alternatively, newly developed theoretical constructs, completely covering the implicit meaning of the code cluster. In the example given above, a new analytical category 'Personality' was developed to reflect

the common contents of the constructed lower-level codes. Particular emphasis was laid on defining categories that are collectively exhaustive and at the same time mutually exclusive (Krippendorff, 2011, p. 98). The code clustering procedure was performed until all constructed codes were assigned to a higher-order category, reflecting a specific theoretical construct. The final coding scheme consists of 13 main categories and 68 subcategories. The coding scheme together with the number of text units attached to those codes are illustrated in Table 4.5.

However, it has to be acknowledged that these findings must be related to the objectives of the inductive research endeavour (Planing, 2014 p. 116). Therefore, conclusions from the empirical results of the content analysis should be drawn only in conjuncture with the research questions (see chapter 4.1.1). They moreover ought to be correlated with existing theoretical and conceptual models in literature for a further refinement of the concepts identified. This convergence process is discussed in the course of the development of the Wearable TAM in chapter 5.

4.3 Interim Implications

The results from the qualitative study give manifold insights concerning the inter-individual adoption decision process in wearable technology markets. In total, 13 theoretical constructs have been developed from the qualitative research phase that capture the selected respondents' perceptions and interrelated beliefs on the intention formation towards wearable technologies. These concepts are supposed to build the ground for deriving the sought Wearable TAM in a theory-driven manner by providing important aspects and determinants of wearable technology acceptance behaviour.

Two out of these 'nominal' categories emerged relate to non-psychographic factors that nonetheless contribute to the body of knowledge in the chosen field. The frequent referrals to profound behavioural changes expected at a societal level thus show that wearables, understood as intelligent *standalone* devices, exert indeed a disruptive effect on habitual patterns of behaviour. They thus involve unique challenges for market preparation including creating awareness and educating prospective consumers about the innovation (Sandberg, 2002, p. 189). Two respondents (I.1, P.88 and I.3, P.9) stated that wearable computing will presumably transform private and business life through an increase of consumer-originated technological devices and models that develop in the consumer space and afterwards gain currency in enterprises. This market-structure-shifting movement that, i.a. also comprises the **Bring Your Own Device** (BYOD) phenomenon is also referred to as 'consumerization of IT' (Fenn & LeHong, 2011, p. 7) and can be regarded as the natural result of a society that is becoming more and more 'digitised' and mobile.

Interestingly, several respondents have made multiple references to the diffusion patterns of smartphones. In particular, two participants pointed to the evidence that it became prestigious to possess an Apple product such as an iPhone or iPod and that they are hence consumed not least because of their symbolic or expressive value (I.1, P.77 and I.2, P.26). That is, the culturally constructed, social meaning associated with those products enables consumers to communicate their identity and social status (Ravasi & Rindova, 2004, p. 3). Another respondent stressed the importance of the iPhone's usability for its commercial launch success and widespread dissemination (I.3, P.29). Drawing conclusions by analogy, wearables should allow for intuitive operation and, additionally, satisfy hedonic needs for self-expression in order to increase their adoption rate. However, it should be kept in mind that one

cannot directly extrapolate from the diffusion patterns of smartphones to the diffusion patterns of wearables (cf. chapter 2.4).

When asked about the current market development and anticipated economic potential of wearable devices, all participants suppose either smart glasses or smartwatches to become most relevant for their stakeholders in the long term. In the short to medium term, smartwatches and fitness bands are expected to continue acquiring the largest share of the market. This backs the findings on the current market situation in chapter 2.4. One respondent believes that smart clothes will lead to tremendous changes particularly in the health sector over the long run, as they will tap completely new possibilities of communication (I.3, P. 94). Yet, in light of these findings it appears to be reasonable to focus on both smartwatches and smart glasses as most prominent technologies for the purpose of the present research project.

As indicated by the frequent referencing to acceptance-related determinants, product growth is actually influenced by various demand factors, such as social acceptability and changes in beliefs. These aspects are summarised into the central phenomenon 'Acceptance behaviour' that denotes the present study's object of cognition, leading back to the initially defined category formation criterion and, accordingly, to the studies research questions. Apart from this, various non-psychographic macro-environmental forces were pointed at, which are, however, outside of the scope of the present study as they cannot be altered by managerial actions. Especially, the points of pricing structures and technical immaturity emerged during the process of coding and analysis. From the latter it can be concluded that the degree of usability may not be measured validly, as the respective technologies still lack sufficient overall maturity and thus require further advances in many fields to comply with technological and human standards. Furthermore, the results show that social influence plays a considerable role in wearable computing adoption processes. From a social network perspective, this suggests that social proof might also have some conative influence on usage decisions in terms of a sociocultural impetus that manifests in a bandwagon-based diffusion gaining momentum.

In this context, for the adoption process to become endogenously self-sustaining it is of paramount importance to achieve a critical mass of adopters first in order to adequately stimulate dynamics in consumer preferences (Lechman, 2015, p. 51). In line with Rogers' diffusion of innovations theory, the earliest consumers to purchase innovations are categorised as innovators, followed by early adopters (see chapter 3.1.1). These individuals are commonly characterised by a relatively high degree of venturesomeness and technical affinity compared to the other members of their social system. This disposition leads to a greater innate willingness to adopt innovative technologies (Rogers, 1983a p. 201). The nexus is well-supported by the present exploratory study, as several respondents stressed the level of personal innovativeness in consumer decision-making by explicitly mentioning 'early adopters' as main target group of prospective consumers (e.g. I.6, P. 39 or I.7, P. 13).

Furthermore, the interview analysis revealed that personality-related correlates of behaviour exert actually an important - albeit indirect - influence on wearable computing acceptance. The most common predisposition to behaviour mentioned by the respondents is the personal relevance or involvement with mobile and wearable computing. Since this factor is deemed to directly interact with compound personality traits (Bosnjak, et al., 2007, p. 599), it may be considered as a more domain-specific trait relevant to consumption behaviour. Additionally, status concerns emerged as another salient socio-psychological variable that affect the decision to adopt wearables.

Category	Constructed Code	References	Sources
Acceptance behaviour	Acceptance	9	4
	Socio-psychographic factors of adoption	11	5
Innovativeness	Level of innovativeness	2	1
	Fear of innovations	2	2
	Early Adopter	3	3
IT security aspects	IT security	4	4
	System reliability	1	1
	Third Party Access	2	1
	Sensitive personal data	4	3
	Surveillance	5	3
	Privacy	11	7
Macro-environment	Technical immaturity	21	7
	Pricing	10	6
	Competitive factors	3	1
	Political and legal aspects	4	3
Perceived Risk	Physical risks	1	1
	Generally risky	1	1
Perceived Usefulness	Relative Advantage	12	5
	Control of networked devices	2	1
	Work support	24	7
	Health	17	5
	Quantified Self	10	4
	Safety	1	1
	Efficiency enhancement	7	4
	Learning aid	25	5
	Error reduction	3	3
	Entertainment	3	2
	Strengthens social relationships	11	4
	Enhancement of self-confidence	5	3
	Gamification	1	1
	More comfort of life	1	1
	Schedule control	5	3
	Many application scenarios	2	2
	Boosts fitness	7	5
	Continuous and persistent logging	4	3

Category	Constructed Code	References	Sources
	More transparency and traceability	1	1
	Ubiquitous connectivity	2	2
Personality	Curiosity	2	2
	Lifestyle	1	1
	Status-Consciousness	4	3
	Open to new ideas and experiences	2	2
	Affective motives	3	3
	Personal involvement	7	4
Pervasiveness	Sensory features (multimodality)	11	5
	Context-awareness	5	3
	Proactive	7	6
	Convenient	9	4
	Hands-free working	8	3
	Information accessibility	9	6
	Seamless integration into everyday life	5	3
	Real-time operation and output	5	3
	Always on	6	5
	Non-distracting	2	2
	Ubiquitous	1	1
Prior Experience	Prior Experience	3	3
	Familiarisation with wearables	3	3
	No personal experience	1	1
Social Influence	Other-directedness, Imitation	2	2
	Reactions of the social environment	1	1
Trust	Trust in consequences of usage	4	3
	Trust in the system's functionality	2	2
Usability	Fashionability and wearing comfort	6	5
	High demands on effectiveness and efficiency	6	3
	Demands on the range of functions	1	1
	Usability	5	3
Behavioural change	Behaviour modification due to continuous monitoring	2	1
	Mergence of private and business life (BYOD)	3	2
	Lives become more "digitized" as media consumption behaviour changes	2	2

Table 4.5: Coding categories of the qualitative study

As can be further seen from the identified categories listed in Table 4.5, the strongest intrapersonal factor that is expected to support the acceptance of wearable computing is *Perceived Usefulness*, primarily attributed to work and learning support. Most respondents named hands-free instruction guidelines and real-time notifications as specific product features that they considered beneficial. Furthermore, the wearables' potential assistance in the field of health and fitness - particularly through offering the possibility of continuous self-monitoring - was variously seen as a clear advantage. Based on the interviews, the usefulness of wearables can be mainly ascribed to the unique attributes of the respective, newly emerged computing paradigm. Theses abstract attributes may be subsumed under the concept of *Pervasiveness*, meaning that this innovative class of IT systems ought to provide ubiquitous as well as context-aware information services and applications unobtrusively to the greatest possible extent in order to generate substantial benefits. Accounting for the main differences between traditional desktop systems and pervasive or ubiquitous computing models, wearables should be seamlessly integrated into the daily life, proactively enhancing all routine activities. This is in line with previous research, which emphasises on the importance of the perceived ubiquity, unobtrusiveness, and context-awareness of emerging technologies (Karaiskos, 2009, p. 83).

Moreover, from the results of the qualitative study it is apparent that the main reason for wearable computing resistance are IT security concerns. This finding backs contemporary Information Systems literature which considers security risks to be a prime inhibitor to technology adoption (see chapter 3.2). In particular, a majority of respondents reported that they would fear privacy risks in view of the fact that wearables would process highly sensitive personal data at an unprecedented rate. Yet, *perceived risks* outside IT security risks have seldom been mentioned, referring to ambiguous threats and physical risks due to possible distractions. The interview statements (e.g. I.5, P. 50 and I.7, P. 51) show furthermore, that trust in the technology itself including its functionality and predictability directly relates to risk perceptions. Besides, based on the interview results consumers' prior experience with a certain technology might lead to a higher acceptance of that system in terms of a greater tolerance towards associated risks and habituation. One participant (I.3, P. 24-27) cites the increasing acceptance of CCTV or Google Street View as a concrete example. Also, the degree of personal innovativeness seems to influence how consumers assess the perceived risk and usefulness of such technologies (e.g. I.3 P. 43 and I.7 P. 13).

4.4 Chapter Conclusions

This chapter was centred on the qualitative approach of the present study, so as to identify important belief groups and holistic insights on adopter perceptions towards wearable computing. The critically appraised theoretical foundations and key concepts in chapter 3 formed thereby the basis for the semi-structured interview guideline. In the course of the explorative research phase, 68 constructed codes rephrasing parts of the source texts and 13 main concepts grouping these codes could be extracted from the interview transcripts. Eleven out of these categories that were found to be particularly relevant in a wearable computing context reflect psychographic factors which all relate to different concepts in Information Systems research.

In sum, the implications from the exploratory study are substantial from the point of view that they deliver unique insights from a qualitative perspective. It is the first study focussing on the social and psychological origins and contexts of wearable computing usage intention. The inductive findings provide not only single belief sets, but

also a holistic perspective on the acceptance behaviour in innovative IoT markets. The empirical results from the expert interviews contribute to Information Systems research by revealing the substantial role of personality traits on the consumer' willingness to adopt wearable computing. Additionally, the elicited significance of IT-related risk perceptions underscores the importance of information security for technology acceptance. Also, this study sheds light on the interplay between the extent of 'perceived pervasiveness' of respective technologies and attitude formation. Therefore, the first three research questions of this thesis (i.e. what are the individual-level drivers, obstacles, and personality-related aspects of wearable computing adoption) can be regarded as being addressed so far. However, it has to be emphasised that the results are not readily generalizable to the broad consumer market, as they are based on a theoretical sample. Rather, they serve as a basis for the theory-based hypotheses derivation and subsequent development of the quantitative study.

5 Theory-driven development of the Wearable Technology Acceptance Model

After having established the relevant theoretical reference points and concepts, this chapter is dedicated to the development of an inter-individual path model of wearable technology acceptance. This model can be understood as a methodological instrument on the basis of which the theoretical acceptance factors, their pathways as well as significant background variables can be investigated in a causal-analytical manner. Overall, the Wearable TAM aims at clarifying correlating effects of the hypothetical constructs and to explain the consumer's intention to adopt wearable technologies.

5.1 Technology Acceptance Model in the Context of Wearable Computing

Building on the results of both the qualitative expert interviews and the findings of prior research in marketing and Information Systems, the causal hypotheses are deduced in the following sections. The integration of convergent conceptual frameworks from different research streams thereby ensures that the sought behavioural model allows instructive conclusions to be inferred for marketing practice. Since contemporary research gaps as well as the results of the qualitative study prompt this, particular attention is directed to commensurable theories in the area of IT security and personality psychology. Subsequently, significant third variables relevant to the investigational domain are identified and coherently incorporated into the total system of hypotheses that interconnects the conceptualised factors of wearable technology acceptance.

5.1.1 Technology Beliefs

The following sections focus on salient cognitive concepts that are particularly relevant in a technology adoption context.

5.1.1.1 Perceived Usefulness

In order to develop appropriate Wearable TAM hypotheses, a robust behavioural model (i.e. theoretical anchor) must first be defined. Due to its efficiency as well as its dominant role within acceptance research (see chapter 3.1.2.3), in the present study TAM served as a basis for successively evolving the research hypotheses. As could be shown, this model is specially geared towards understanding acceptance behaviour in technology markets. In addition, this study implemented further complementary theoretical concepts. Augmenting the TAM with additional constructs may counteract the conceptual criticism that – due to its universal applicability in Information Systems research – the originary causal network features only limited transferability to specific problem areas. An integrative modelling approach assumingly enables to make more precise assertions about attitude formation within the newly emerged IT application domain under consideration. Moreover, the theory-driven reconceptualization of the original TAM variables in the subsequent passages may lead to a higher specificity of

the sought explanatory model. The adapted nomological network is thus expected to explain a greater amount of variance in wearable technology acceptance behaviour.

In the course of the systematic model modification, the guiding research question concerning the socio-psychological antecedents of ICT adoption has primarily been addressed. Since the wearables market launch is still progressing relatively slowly (McNutt, 2015), the actual usage behaviour as an originally provided TAM construct had to be excluded on research economic reasons. Rather, the intra-attitudinal structure should be established first, focussing on the dependent criterion variable of *behavioural intention to use* wearable computers. As the most proximate predictor of behaviour (Ajzen, 1991, p. 181), in the following this conative component of attitude is conceptually regarded as an acceptance response to adopt wearables. Consequently, the tripartite model of attitude structure discussed in chapter 3.1.2.1 – where intention represents a structurally separated latent construct – constitutes a suitable explanatory approach. Herein, the evaluative judgement subsuming affective and cognitive properties of attitude exerts a direct, positive effect on individual's intention to act.

Nevertheless, the decision to adopt innovative ICT products is often considered to be inherently fraught with risk and comparably utilitarian in nature (Doole, et al., 1997 p. 52; Kim, et al., 2009 p. 68). Therefore, it can be expected that IT adoption requires a relatively high level of careful consideration in terms of a more rational choice decision. This assumption is supported by various acceptance studies, which indicate that the decision to adopt ICT systems is primarily driven by a cognitive cost-benefit analysis (Chun, et al., 2012, p. 474). In addition, several studies found that attitude did not fully mediate the effect of technology beliefs on usage intentions (Burton, et al., 2005 p. 59). Therefore, the most common modelling approach in technology acceptance literature that excludes the affective attitude component from decision-making (cf. Yang & Yoo, 2004, p. 20) is followed in this study.

Furthermore, in technology acceptance research the 'perceived ease of use' construct has been observed to be a relevant predictor of attitude in a wider variety of research. From a cognition-theoretical viewpoint, however, predictive validity of this exogenous construct is considerably higher in such instances where users already have product knowledge (Venkatesh, et al., 1996 p. 465). In the absence of previous experiences with innovative technologies, decision-makers have to rely on more abstract product criteria as decision heuristics (Park & Lessig, 1981, p. 223). Correspondingly, some prior studies in the health care segment suggest that having no or only little practice in the use of an IT system leads to a poorer estimate of user-friendliness. On the other hand, increasing hands-on experience might completely diminish the importance of usability for acceptance and use (Holden, et al., 2010). The frequent lack of empirical evidence for an ease of use-attitude link (see e.g. Chau, et al., 2001 p. 712, or Agarwal, et al., 1997 p. 572) has some researchers even led to conclude that "no amount of ease of use (EOU) will compensate for low usefulness" (Keil, et al., 1995 p. 89). With regard to dynamically-discontinuous and radical innovations in fairly fragmented wearable computing markets, it has to be assumed that statements on the usability of wearables may not yet be made validly. The different device types and products differ too strongly in regard to their functional and ergonomic properties. All the more so as one finding of the qualitative study suggests that several wearable technology solutions (particularly smart glasses and smart textiles) still lack sufficient overall maturity. This renders a general statement on the usability of wearable technologies virtually impossible. Moreover, systems tested in the past (e.g. e-mail programmes, e-commerce applications, internet banking or tools for computer-aided software engineering) greatly differ from future information technologies like wearables in

terms of pervasiveness, context-awareness and the way of human-computer interaction. Therefore, Röcker recommends in (2010, p. 241) to identify new factors that supersede the ease of use construct by explicitly accounting for the characteristics of future ubiquitous systems (in the present study this is achieved by including the pervasiveness construct as outlined in section 3.3.2). Thus, ease of use was excluded from the structural model for methodological reasons, as well.

Besides the above outlined causal effect of the perceived system's ergonomics on usage intention, TAM posits further a perceived usefulness concept. According to Rogers' diffusion of innovations theory, the perceived superiority of an innovation (which may stem from the product's enhanced capabilities) directly determines the evaluative judgement towards the usage of the given system. This also includes anticipated behavioural consequences in the sense of extrinsic rewards that accrue as a result of product usage, for example through increases in time savings and efficiency gains (Bagozzi, et al., 1999; Bagozzi, et al., 1992 p. 662; Wünderlich, 2009 p. 137). The relevance of extrinsic motivations in decision-making manifests in the fact that benefits serve as prime orientation and evaluation criteria in decision processes (Akturan & Tezcan, 2012, p. 449). Actually, several meta-studies have shown that perceived usefulness is the most robust predictor of technology acceptance in Information Systems application domains (e.g. Ma & Liu, 2004).

In the context of wearable computing acceptance, perceived usefulness is understood as the degree to which consumers belief that using a wearable computing device would be utilitarian in enhancing one's life. Borrowing from a quantitative social study among over 4,000 UK and US adults, this latent variable is conceptualised as a multidimensional construct, reflecting several salient benefits of wearables which primarily relate to enhancements of living conditions (Brauer & Barth, 2013). In particular, this abstract construct is theorised to consist of the five formative subdimensions 'Enhancement of personal abilities', 'Improvement of health and fitness', 'Enhancement of self-confidence', 'More control of life', and 'Enhancement of social relations'. This conceptualisation allows to adapt the tradition-rich usefulness construct to the present study context and to gain more differential insights with regard to the underlying causes of usefulness perceptions.

In sum, if a consumer believes that a wearable would be useful, he or she is more likely to intent to use it. Assuming that intentions to use are proximate predictors of future usage behaviour and considering the degree of specificity of perceived usefulness and the behavioural criterion, the following causal hypothesis is proposed:

H_1: Increased consumer's perception of the usefulness of wearable computing will result in an increase in the intention to use a wearable computing device.

5.1.1.2 Perceived IT Security Risks and Antecedents

Especially in the course of *limited* and *extensive* purchase decision-making processes, the cost/benefit ratio plays a major role in conscious attitude formation. Drawing on utility theory, the consumer's perceived net value represents a dichotomous characteristic, composed of benefits and sacrifices (Snoj, et al., 2004, p. 157). As discussed in chapter 3.2, perceived sacrifices have empirically been shown to consist of diverse non-monetary costs associated with product acquisition and usage. Moreover, risk perceptions have variously been found to constitute a crucial impediment to the rate of adoption (Planing, 2014 p. 65).

Within the exploratory study, particularly IT security threats (linked to a set of legal requirements) emerged as a dominant topic in the context of B2C markets (see chapter 4.3). Nonetheless, in published empirical acceptance studies, the influence of traditional security goals on behavioural intention to use an information system, with one notable exception (see Hartono et al., 2014), has not yet been analysed from a consumer perspective. Extant quantitative research related to subjective security and rooted in TAM conceptualise consumer perceptions of security commonly as unidimensional, e.g. as 'website security'. For instance, in studies on electronic commerce empirical evidence could be provided for the correlative relationship between Web security concerns and the usage of the electronic medium for purchasing (Salisbury, et al., 2001), between perceived security with regard to the handling of personal data and the loyalty shown to a Web site (Flavián & Guinalíu, 2006), and between subjective information security of electronic commerce transactions and the acceptance of online transactions (Suh & Han, 2002; Chellappa & Pavlou, 2002).

In this study, perceived security is regarded as the subjective probability with which consumers believe that relevant information services will be timely available and personal data will not be viewed, stored, and manipulated during processing, storage or transfer by inappropriate parties in a manner consistent with their confident expectations. Thus, the developed conceptual domain of security implies a multidimensional construct, linking objective measures to subjective perceptions as introduced by Hartono et al. (2014). If the customer deems the technology-driven environment to be confidential, integer and constantly available, he or she is more likely to intent to use the system. Proceeding from the assumption, that perceived security is an abstract, second-order formed attribute, the following correlative relationship is hypothesised:

H_2: Decreased consumer's perception of the security risk of wearable computing will result in an increase in the intention to use a wearable computing device.

In sum, as a result of the TAM modification along the above findings, the structural model illustrated in Figure 5.1 emerges. Albeit this conceptual framework readily provides a solid theoretical basis, the high generalisability of its statements across any technology adoption context inevitably leads to a less explanatory power as discussed previously. Consequently, the partial model developed so far is ill-suited to address the above managerial problems, yet. Therefore, the psychological process intervening between the behavioural intention to adopt wearables and environmental stimuli has to be explicated more fine-grained by introducing additional predictors.

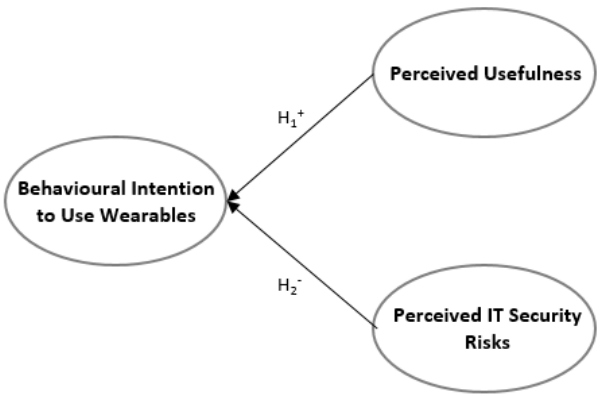

Figure 5.1: Conceptual frame of the sought structural model based on TAM

In behavioural economics, sociological and psychological sciences, subjective risk perceptions are conceptually closely related to the notion of trust (Rousseau, et al., 1998, p. 395). This latent connection has already been demonstrated in numerous empirical studies, e.g. in Mayer et al. (1995). Up to now, however, in technology-driven environments trust has mostly been interpreted as a measure of interpersonal relations, focussing on the trustworthiness of e.g. e-vendors, institutions or website owners (see chapter 3.2.3.1). On the contrary, recent research endeavours clearly indicate a catalytic role of technology trust in attitude formation towards adoption decisions fraught with risk (Thatcher, et al., 2011). Accordingly, Lee et al. (2011, p. 228) could show that business user's willingness to switch from offline to online service channels increased when they placed trust in the internet technology itself. In line with this finding, Planing (2014, p. 124) exploratively identified trust in technology to be a major motive for the acceptance of advanced driver-assistance systems. From a nomological viewpoint, in marketing and management literature trust is commonly assumed to be a direct antecedent of both attitude and perceived risk (Lankton, et al., 2015, p. 885).

To recap the above discussion, in this study trust in technology refers to the trust the consumer has in wearable computing devices and services. Because multiple empirical studies were able to prove evidence that consumer's trust positively affects their willingness to engage in a risk-taking behaviour, the subsequent relationship is postulated:

H_3: Increased consumer's perception of trust in wearable computing will result in an increase in the intention to use a wearable computing device.

Since trust becomes intrinsically relevant in situations where people have incomplete control over the outcome, as the level of trust increases consumers are likely to perceive less ambiguity and risk than if trust were absent (Kim, et al., 2008, p. 547). Therefore, the effect of trust on consumer's intention to use wearables is supposed to be mediated by perceived security risks. Given this relationship and responding to the call for a 'deepening' of the TAM in the sense of reconceptualising its core predictors and introducing new exogenous variables (Bagozzi, 2007, p. 244), the following mediation hypothesis is proposed:

H_{3a}: The relationship between the level of trust towards wearable computing and the intention to use wearables is mediated by perceived security risk.

Still, the above modified TAM framework does not account for the distinctive characteristics of the newly emerged Information Systems class of pervasive computing. For this reason, further suitable exogenous variables should be considered, so as to holistically explain the intention to employ pervasive or ubiquitous computing systems. Karaiskos hence postulates in (2009) a novel pervasiveness construct specifically defined to meet the inherent particularities of this new computing paradigm (see chapter 3.3.2). Thereby, pervasiveness is deemed to determine exploratory variables in research models of technology acceptance (Karaiskos, 2009, p. 147 ff.; Koondhar, et al., 2015, p. 101). Karaiskos stresses the relevance to augment existing theories from the technology acceptance stream with the concept of pervasiveness. Ultimately, knowledge of the demand side in ubiquitous computing diffusion follows from an understanding of the properties that define the pervasive nature of a given information system (Karaiskos, 2009, p. 77).

Motivated by this theoretical and practical interest, this study also implements a pervasiveness perspective into the cause-and-effect chain of the sought Wearable TAM. In this way it substitutes the original ease of use component. The pervasiveness concept is regarded as being constituted by the trichotomy of perceived ubiquity, unobtrusiveness and context awareness of a wearable technology, determining the consumer's cognition-based beliefs (i.e. perceived usefulness). Thus, the following two conditional sentences are proposed:

H_4: Increased consumer's perception of the pervasiveness of wearable computing devices will result in an increase in the intention to use a wearable computing device.

H_{4a}: The relationship between the level of consumer's perception of the pervasiveness of wearable computing and the intention to use wearables is mediated by perceived usefulness.

5.2 Augmenting the TAM with Personality Measures

In marketing literature, the consumer's psychological predispositions are well-recognised as relevant drivers of decision-making behaviour (Peter, 1979, p. 13; Allport, 1961, p. 179; Baumgartner, 2002, p. 286). Correspondingly, by referring to the concept of innovativeness the expert interviews implicitly suggest that adopter's personal characteristics are of considerable importance for the individual duration of adoption (see chapter 3.1.1). In line with this finding, Ajzen posits in (2005, p. 6) that personality factors describe response tendencies in a given domain and are thus expected to find expression in individual behaviour patterns. Therefore, as personal predispositions are assumed to play a ubiquitous role in human cognition, it is plausible to suppose that traits affect at least partially Information Systems-related processes (Devaraj, et al., 2008, p. 94). Nonetheless, personality variables have seldom been examined within the scope of acceptance research (Zhou & Lu, 2011, p. 545), which is why the following sections address this issue.

5.2.1 Elemental Traits

In personality and social psychology, a plethora of personality traits has been identified and conceptualised from various theoretical perspectives and at numerous abstraction levels (John & Srivastava, 1999, p. 102). Commonly, personality is defined as "the dynamic organization within the individual of those psycho-physiological systems that determine his characteristic behaviour and thought" (Allport, 1961, p. 28). For the purpose of the present study, this definition is adopted.

Despite the conceptual diversity and scientific pluralism, personality psychologists have reached a consensus that the personality structure in terms of endurable individual differences may most appropriately be portrayed by the *Big Five* trait taxonomy, alternatively also referred to as **Five Factor Model** (FFM) of personality (McCrae & Costa, 1997, p. 509; Moore & McElroy, 2012, p. 268). This descriptive model both comprehensively and parsimoniously reflects the most salient, psychometrically sound dimensions of personality along five bipolar trait concepts in a common classification schema. These five domains of personality are considered to be inferable from external, observable cues. Even though there is a persistent lack on agreement regarding the exact labels for

each dimension, the following terms are increasingly employed in personality psychology literature (Devaraj, et al., 2008, p. 94; McElroy, et al., 2007, p. 811; Barrick, et al., 2001, p. 11):

- Extraversion – Introversion: This personality facet indicates the sociability and talkativeness of a person. Extraverts intrinsically place a high value on interpersonal relationships.
- Agreeableness – Disagreeableness: This dimension semantically relates to prosocial attributes such as trust and cooperativeness.
- Conscientiousness – Lack of Direction: Conscientious personalities are highly goal-directed, disciplined and responsible-minded. Those high on conscientiousness feature a higher level of self-control reflected in their need for achievement and order.
- Neuroticism – Emotional Stability: This trait relates to the internal emotional stability. Standard attributes of this dimension include anxiety, moodiness and irritability. Highly neurotic individuals tend to be emotionally reactive and distrustful.
- Openness to Experiences – Closedness to Experiences: Those who score high in openness tend to hold unconventional values, are more curious and willing to explore new ideas and embrace novel approaches.

According to Briggs (1992, p. 254), the five-factor classification schema enjoys a substantial lead over its primary competitors describing the universe of trait terms. The scholar demarcates this well-substantiated and agreed-upon framework for the structure of personality as "the model of choice for the researcher wanting to represent the domain of personality variables broadly and systematically" (ibid.). Subsequent research found the FFM to be the most useful taxonomy in personality research (Barrick, et al., 2001, p. 11). Considering this theoretical support, it seems reasonable to seize this framework in the course of the present study as well.

Empirical research on the influence of personality in consumer behaviour contexts supports the effect of these cardinal traits on behavioural intention. For example, Svendsen et al. (2013) proved a significant interrelationship between the big five personality variables and the TAM beliefs, suggesting that dispositional correlates of the willingness to use ICT exist. Accordingly, Moore and McElroy (2012) empirically showed that traits exert influence on Facebook usage patterns and content. By focussing on collaborative technologies, Devaraj and colleagues (2008) incorporated the five-factor model into the TAM and where thereby able to enhance the predictive power of the original Information Systems model.

Conceptually, in psychology literature the personality structure is understood as a hierarchical system of traits at different levels of specificity (Costa & McCrae, 1995, p. 22; Baumgartner, 2002, p. 286). At the broadest level of abstraction, groups of covarying elemental traits represent the most basic temporally and situationally invariant predispositions including the big five personality traits (Gosling, et al., 2003, p. 506; Goldberg, 1999, p. 9). Each factor subsumes several more concrete facets at a lower-order taxonomy, which in turn summarise a number of even more specific traits. Whilst a general consensus has been achieved on the five psychological traits at the top of the hierarchy, there is still an ongoing controversy about the lower-level subcomponents (Judge, et al., 2013, p. 875).

In an attempt to bridge the theoretical gap between overarching intrapsychic predispositions and more concrete consumption-relevant traits in an integrative framework, Mowen (2000) propose a meta-theoretic model of motivation and personality, namely the 3M model. This fully mediated model posits an ordered nomological net composed of elemental, compound, situational, and surface traits. **Elemental traits** exist at the deepest level of personality and include the big five dimensions, whereas **compound traits** such as the need for cognition emerge from the interplay between elemental traits, culture, subculture and the individual socialisation history (Mowen, 2004, p. 53 f.). **Situational traits** are defined as dispositions to express consistent patterns of behaviour which apply to general situational contexts. Situational traits are closely related to the concept of involvement (Bosnjak, et al., 2007, p. 599). Finally, **surface traits** at the most concrete hierarchical level possess strong conative and affective properties. Resulting from the effects of elemental, compound, and situational dispositions, consumer's surface traits are highly predictive of behaviour and thus frequently associated with the concept of behavioural intention (ibid.). Figure 5.2 exemplifies the 3M model.

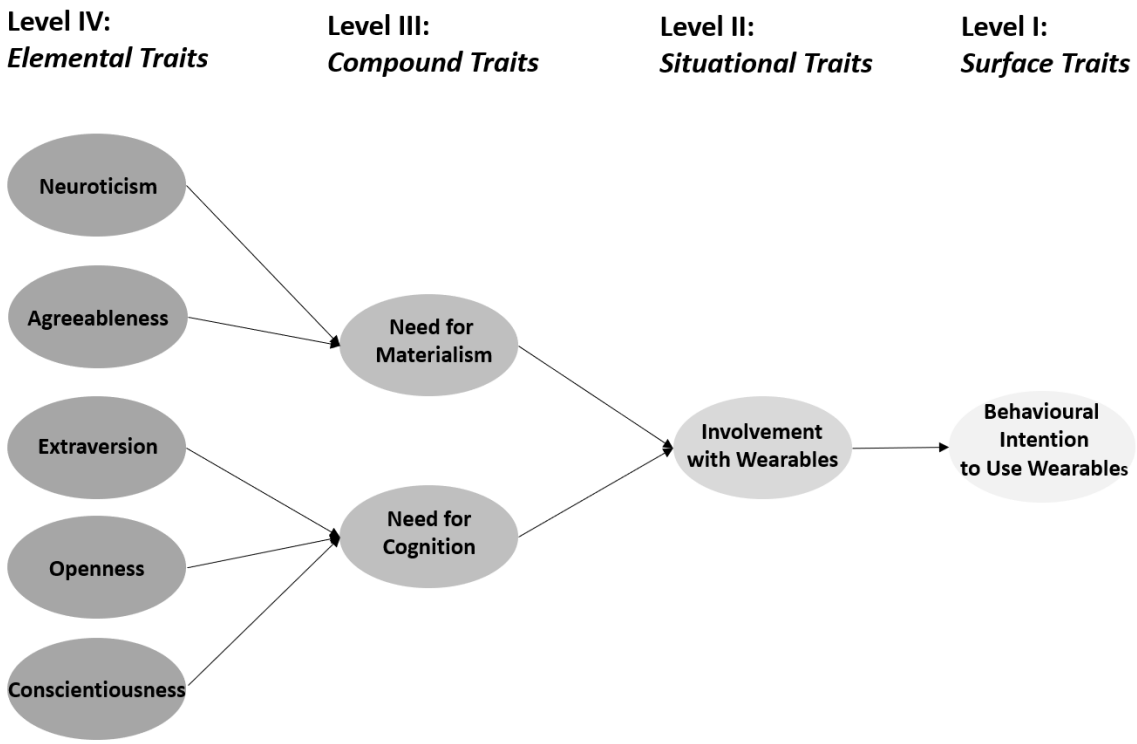

Figure 5.2: Exemplified application of the 3M model

The specific role of personality variables in a technology acceptance context can be derived from the theoretical basis of the TAM (Devaraj, et al., 2008 p. 95). The TRA as a source model of TAM considers traits to be external variables which are completely mediated by endogenous variables. Personality-related constructs exert therefore only an indirect influence on behavioural intention by affecting factors that are more closely linked to the target variable (Ajzen, 1991 p. 181). From this it follows that the impact of broader general traits is strongly attenuated by the presence of more immediate personality factors. Transferring this line of reasoning to the TAM, the 3M framework may be integrated into Information Systems models by conceptualising the intention to use a system as a highly context-specific disposition that serves as a connecting factor for hierarchically less specific traits. Figure 5.3 illustrates the incorporation of the 3M model into an integrated technology acceptance model. The

present study follows that approach and seeks to synthesise a comprehensive research framework that combines both conceptual models. For this purpose, the next sections deal with the specification and adaption of compound, situational, and surface traits to the given study subject.

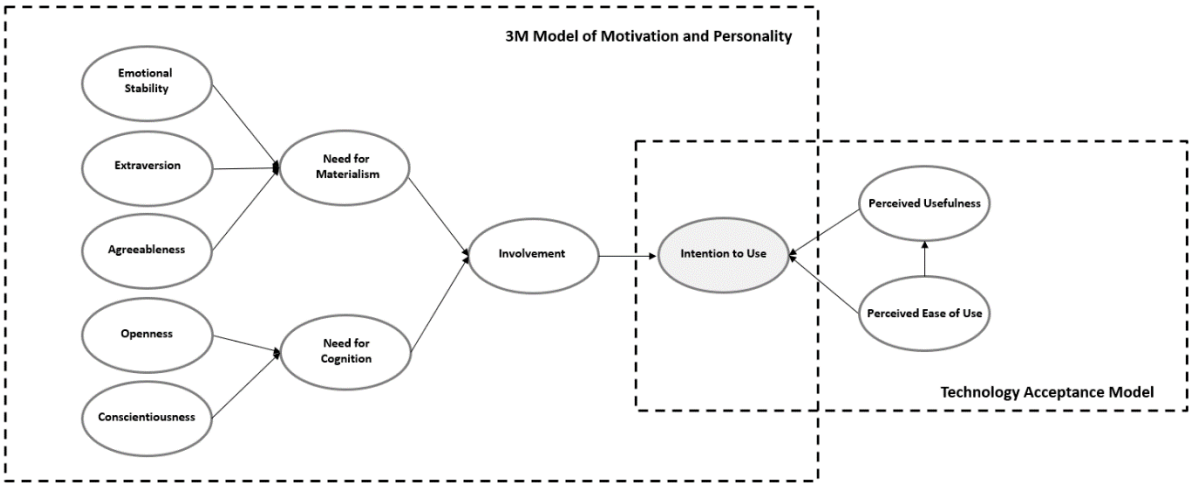

Figure 5.3: Integration of the 3M model into TAM

5.2.2 Compound Traits

Consistent with the results of the qualitative study, suggesting that status-consciousness (i.e. a concern for social recognition, esteem, or prestige) may also play a considerable role in wearable computing adoption, in consumer settings Richins (1987, p. 352) particularly emphasise the relevance of materialism as "the tendency to view worldly possessions as important sources of satisfaction in life" (Belk & Pollay, 1985, p. 394). Since there are pervasive behaviour patterns including buying and consumption behaviours associated with materialism (Richins, et al., 1992), this group comprises a particularly important market segment.

As conceptualised by Belk and Pollay, materialism is a latent construct that relates to personality and self-concept issues (1985, p. 396). In accordance, Mowen and Spears (1999, p. 419) could empirically confirm that the need for material resources is strongly associated with consumer's emotional stability. Consequently, it may be inferred that neuroticism in terms of an opposite pole of emotional stability is likewise directly correlated with materialism. Given that materialism reflects a tendency towards status-consciousness, the subsequent hypothesis is hence proposed:

H_5: Increased consumer's level of neuroticism will result in an increase in consumer materialism.

Moreover, past research has established that humans have a psychogenic need for arousal that describes a behaviourally-relevant individual characteristic having importance in consumer contexts (Mehrabian & Russell, 1974; Zuckerman, 1979; Mowen & Spears, 1999, p. 413). This psychological phenomenon refers to one's inclination to continuously seek new experiences and sensations in order to maintain an optimal level of stimulation. In turn, the optimal level depends on the individual pharmacological characteristics of the limbic reward system (Zuckerman, 2014 p. 10; Schiffman, et al., 2009 p. 145). Those subjects with high optimal levels for arousal are generally more responsive to novel stimuli and, hence, show a greater willingness to try new products and to be innovative. As

the homeostatic need for activation empirically relates to particular configurations of behaviours, interests and social roles, it is assumed that this personality trait is also reflected in information and media consumption patterns (Donohew, et al., 1987, p. 256). Correspondingly, Donavan et al. (2005, p. 37) factor-analytically identified arousal needs as important personality-related antecedents of sports fan behaviour. However, the need for activation has empirically been found to be reflected among others by instrumental materialism in terms of an innate pursuit of arousal (Richins & Dawson, 1992, p. 305). For the sake of explanatory efficiency of the proposed correlational framework, the need for arousal has hence been substituted by the construct of consumer materialism.

In causal terms, by terminologically drawing upon Mowen's 3M model, Bosnjak et al. (2007) conceptualised the arousal construct as a compound trait that is directly affected by the agreeableness (in the sense of amiability and community-orientation) of a person. They could empirically demonstrate a negative relationship between both latent constructs (2007, p. 601). By analogy, it may be inferred that an interrelationship between the focal exogenous FFM personality variable and materialistic values actually exists. This theoretical supposition has already received strong experiential support in social research (Otero-López & Villardefrancos, 2013 p. 770). Specifically, it was found that agreeableness has a great explanatory capability on materialism (ibid.). Therefore, the following cause and effect chain is a priori proposed:

H_6: Decreased consumer's level of agreeableness will result in an increase in consumer materialism.

Furthermore, borrowing from information economics and cognitive costs theories, individual differences in need for cognition appear as another promising personality factor (Cacioppo, et al., 1983, p. 806; Chatterjee, et al., 2005, p. 1363). In this context, literature emphasises on the information asymmetry in endogenously uncertain markets and the resulting search and evaluation costs incurred on consumer-side, which precede initial purchase decisions (Wankhade & Dabade, 2010, p. 10). Vendees have to employ time- and money-consuming information acquisition activities for the sake of a reduction of product uncertainty. This theorisation suggests that the willingness to adopt innovations may covary with the behavioural disposition to engage in effortful thinking as a motivational antecedent of information search efforts (Verplanken, et al., 1992, p. 130).

Subjects with higher values on need for cognition have a chronic tendency to spontaneously engage in cognitively demanding activities and are more inclined to apply deeper information processing strategies (Petty & Cacioppo, 1986, p. 674). As in the case for other emotional and cognitive personality-related factors, this psychological phenomenon has important managerial implications for designing convincing marketing communication policies. For instance, the persuasive power of a product's quality indicators (i.e. quality signals in terms of decision simplifying heuristics such as warranties and certifications) significantly varies depending upon the consumers' need for cognition (Chatterjee, et al., 2002, p. 228). Consumers high in cognition needs are likely to spend more time searching and processing product-related, factual information, whereas those relatively low in need for cognition tend to be more attracted by peripheral cues of a message.

In empirical terms, research on consumers' on-line shopping intention supports the presumed causal relationship between need for cognition and attitude formation. Bosnjak et al. (2007) identify this construct as a strong driver of consumer adoption of the internet in terms of a product purchase channel. In accordance with this finding, Mowen understands this cognitive style construct as a precursor of certain situational traits such as value consciousness. He deems this variable to be closely related to the elemental trait of openness to experience (2000,

p. 72). Further, in line with previous research (e.g. Tuten and Bosnjak, 2001, p. 395), Fleischhauer et al. (2010, p. 12) observed need for cognition to be positively correlated with openness, extraversion, and conscientiousness. Under the assumption that the need for cognition may exist at the compound trait level, the subsequent three hypotheses can be formulated:

H_7: Increased consumer's level of openness to experience will result in an increase in the need for cognition.

H_8: Increased consumer's level of extraversion will result in an increase in the need for cognition.

H_9: Increased consumer's level of conscientiousness will result in an increase in the need for cognition.

5.2.3 Situational and Surface Traits

In compliance with the correspondence principle (see chapter 3.1.2.1), empirical research findings suggest that the specificity of overt action must meet the specificity of the independent trait construct, which leads to consistent attitudinal and behavioural patterns within narrower contexts (e.g. Dash et al. (1976) and Schaninger (1976)). Therefore, after having defined the global personality domains in terms of the 'big five' at the deepest, most abstract hierarchical level of consumer personality as well as the more specific compound traits (need for materialism and need for cognition) formed by the underlying elemental traits, adequate, more consumption-related predispositions should be specified.

Among the situational trait level of the 3M framework, the involvement concept has repeatedly been included in Information Systems and consumer behaviour literature. Generally, involvement is broadly defined as perceived personal relevance of a stimulus or situation. This causal or motivational variable explains different phenomena of purchasing behaviour, especially the intensity of the internal information processing and information search behaviour, the nature of the exogenous communication impact (emotional or cognitive), and, consequently, the individual attitude formation (Laurent & Kapferer, 1985, p. 42; Petty, et al., 1983, p. 137). According to Mitchell's frequently adopted terminology, involvement represents an "[…] internal state variable that indicates the amount of arousal, interest or drive evoked by a particular stimulus or situation" (1979, p. 194). In marketing theory, this construct is considered an individual difference variable with various consequences on consumer's purchase and communication behaviour (Laurent & Kapferer, 1985, p. 42).

With reference to their implicit temporal patterns, the antecedents preceding involvement are supposed to categorise this concept into a person, a stimulus factor (i.e. product), as well as a situation-related construct type (Zaichkowsky, 1986, p. 5; Bloch & Richins, 1983, p. 70). Whilst the first two categories are relatively independent from time and thus refer to an enduring involvement (i.e. a general and permanent concern), situational involvement marks a temporary amplification of product importance perceptions, typically within the time frame of a purchase decision (Havitz & Howard, 1995, p. 256). As the present research work primarily focuses on general acceptance of a new computing paradigm, transient situational elements of involvement such as cost features or the surrounding environment has not been taken into account in this study. Rather, considering that the subject of investigation references a novel Information Systems class, an enduring involvement at product class level becomes foregrounded. Accordingly, previous research in the Information Systems field has already acknowledged that a high degree of involvement with the product class correlates with a greater use of mobile

services (Malik, et al., 2013, p. 111). It must be noticed here, that even though product characteristics play an important role, product involvement and, correspondingly, product class involvement varies systematically across individual consumers (Gu, et al., 2012, p. 183).

Furthermore, there is a long tradition in consumer behaviour literature to distinguish between cognitive and affective or ego involvement (Park & Young, 1983, p. 320; Swaminathan, et al., 1996, p. 52). Affective involvement, on the one hand, relates to the nexus between the attitude object and the domain of one's ego. It is evoked by a more *value-expressive motive*, stressing the individual's feelings and arousal (Zaichkowsky, 1994, p. 60). Correspondingly, the qualitative study results suggest that emotional and hedonistic motives, which are associated with affective involvement in literature (Putrevu, et al., 1994 p. 79), intrinsically determine the behavioural intent to use an information system. Cognitive or issue involvement, on the other hand, relates to the extent to which an attitude object may have important consequences for consumers, stressing the individual's informational processing activities evoked by more *utilitarian motives*. This dichotomy of involvement is usually justified by a hemispheric lateralization explanation. According to this perspective, cognitive involvement induces intense processing of factual information by the left brain, whereas affective involvement is characterised by right-brain processing of symbolic or hedonic quality dimensions (Mittal, 1987 p. 42; Putrevu, et al., 1994 p. 79). Consequently, communication strategies should emphasis either on a product's functional attributes or rather appeal emotional motivations (Kim, et al., 2008, p. 39).

Given the valuable managerial implications derivable from each facet of involvement, affective and cognitive correlates of commitment behaviour should be considered individually in the context of wearable technology acceptance. However, empirical evidence has shown that the affective dimension is the sole facet of involvement that significantly predicts online buying intentions (Bosnjak, et al., 2007 p. 602). Moreover, considering that cognitive involvement resembles situational involvement and may raise empirical concerns in regard to its potential collinearity with the cognitive component of attitude (Huang, 2009 p. 97), this thesis approaches affective involvement. In an e-commerce context, Wang et al. (2006, p. 1366) have empirically demonstrated that consumers' cognitive style and involvement level significantly interact with each other and directly affect the consumers' decision-making. Correspondingly, according to recent studies, at compound trait level affective involvement is determined by both the level of consumer materialism and need for cognition (Bosnjak, et al., 2007 p. 603). Hence, the subsequent both hypotheses are derived:

H_{10}: Increased consumer's level of materialism will result in an increase in affective involvement.

H_{11}: Increased consumer's need for cognition will result in an increase in affective involvement.

Finally, at surface trait level the hierarchical model should integrate more specific, consumption-related constructs as stated before. Therefore, in the context of wearable computing acceptance the behavioural intention towards the adoption and utilisation of respective technologies should be focused. In accordance with this, previous research has related affective involvement with the intention to shop online (Bosnjak, et al., 2007 p. 602). Recalling that in the frame of this study behavioural intention is understood as proximate predictor of future wearable technologies usage, the following hypothesis is thus derived:

H_{12}: Increased consumer's affective involvement will result in an increase in the intention to use a wearable computing device.

5.3 Moderating Variables

Depending upon the heterogeneity of a study population, the defined causal relationships might lead to divergent results, i.e. the strength of the relationship between two study constructs can hinge on the value of an interacting third variable (Hair, et al., 2016 p. 243). In this context, moderating variables can provide valuable insights since they allow for a differentiated analysis of cause-and-effect chains (Frazier, et al., 2004, p. 116). Such segmentation variables influence the strength (and potentially even the direction) of the causal relationship between a predictor of interest and its criterion variable, without necessarily being explainable by the given structural model. Thus, the integration of moderating variables may provide clues as to under what conditions the explained variation of behavioural intent increases. Within the scope of the present research, especially moderating effects on intention formation as focal behavioural response are of particular relevance. Besides sociodemographic factors such as age, gender, and education background, psychographic variables can generally be applied (Baron, et al., 1986 p. 1174). In a technology adoption context, particularly adopter-specific characteristics appear to be more revealing contextual factors. Therefore, two moderating variables which were alluded to in the exploratory study and which are of special significance to the proposed correlative framework are discussed in the following.

In innovation research, the individual difference variable of **innovativeness** proclaimed by Rogers has variously proved to be of vital importance (Rogers, 2010 p. 268; Steffens, et al., 1992 p. 12). It describes the individual rate of adoption and serves therefore as a segmentation variable that dichotomises a given consumer population into innovators and imitators (or non-innovators) who each possesses different response characteristics to innovations. This is in line with the expert interview results, which clearly suggest that personal innovativeness strongly influences the attitude formation towards wearables. Yet, it is important to note that in marketing and innovation literature a conceptual distinction is commonly drawn between general and domain-specific innovativeness (Varma Citrin, et al., 2000, p. 295). For instance, a vendee's propensity to innovate in the market for consumer electronics does not indicate anything about his or her pioneering behaviour towards arts or fashion. It is clear from this that an innate global innovativeness has only poor predictive power if applied to specific areas of decision-making. Moreover, a general willingness to change is hypothesised to be possessed, to a greater or lesser extent, by all individuals (Hirschman, 1980, p. 284). Otherwise, consumer behaviour would comprise a series of strongly routinized buying responses to a static set of products. Therefrom, in the further course of this dissertation innovativeness is understood as a product category-related measure.

Agarwal and Prasad claim that personal innovativeness in the domain of Information Technology acts as a key moderator variable on the dependency structures of the intention to adopt any new IT system (1998, p. 206). The innovation scholars point out that this trait induces relatively pronounced risk preferences as a moderator of the consequences of perceptions (ibid.). It thus follows that two individuals showing the same level of utility perception may exhibit different conative reactions insofar their propensity to innovate diverges. In conformity with the significant empirical findings in prior studies, the following both moderating effects are posited:

H_{M1}: The relationship between the perceived usefulness of wearable computing and the behavioural intention to adopt is positively moderated by the product category-related innovativeness.

H_{M2}: The relationship between the perceived security risk of wearable computing and the behavioural intention to adopt is negatively moderated by the product category-related innovativeness.

Beyond this, from the exploratory study the **personal experience** comes as a further potential moderating variable more to the fore. It became apparent that individuals who have had more prior experiences with wearable computing tend to give a more positive evaluation of wearables. Accordingly, past empirical research provides evidence that the impact of the antecedents of IT usage intention changes with end-users' level of experience (Gefen, et al., 2003b p. 307; Venkatesh, et al., 2003 p. 442). Hence, as users get familiar with an information system and learn more of its capabilities, they become more confident towards the focal technology.

Scholars in the field argue that the increased acquaintance with an IT system enhances the user's understanding of the interface and potential benefits from the system become more obvious (Rahman, et al., 2011, p. 271). Moreover, experience-based beliefs are assumed to be more readily accessible in memory, what results in a stronger attitude-behaviour-nexus (Gefen, et al., 2003b, p. 310). Thus, theory suggests that the correlation between utility perceptions and conative behaviour would be stronger for experienced users than for novices. In technology acceptance literature, the concept of experience is delimited in terms of either the frequency of prior usage or the general familiarity with a target system in terms of the level of general product knowledge (Castañeda, et al., 2007 p. 386; Planing, 2014 p. 153). As wearable computers are still in their infancy, the latter definition will be employed during the further work.

In light of the above evidence implying that product familiarity has an impact on the relative importance of attitudinal components, the correlative framework developed so far should be refined based on the extent of end-users' experience. Thus, the next both moderation hypothesises are formulised:

H_{M3}: The relationship between the perceived usefulness of wearable computing and the behavioural intention to adopt is positively moderated by the level of personal experience.

H_{M4}: The relationship between the perception of the security risk of wearable computing and the behavioural intention to adopt is negatively moderated by the level of personal experience.

Figure 5.4 illustrates the moderated relationships inherent to the formulated research model.

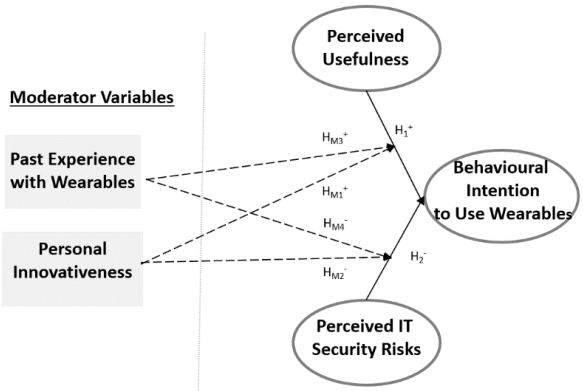

Figure 5.4: Hypothesised moderated relationships

5.4 Synthesis of Empirical and Theoretical Findings

The successively derived structural model conceptualises the target construct *intention to adopt wearable computing* as a proxy of acceptance behaviour that reflects a direct consequence of cognitive beliefs and product category involvement. All in all, drawing on the results of the qualitative study and the findings of prior research, the explanatory research model as depicted in Figure 5.5 (i.e. the Wearable TAM) could be deduced stepwise. In this acceptance model, the behavioural intent to use wearables is defined as a causal effect of cognitive beliefs regarding the degree of both usefulness and pervasiveness of wearable computing. The latent variable of perceived usefulness is considered a multifaceted construct, reflecting several salient benefits of wearables which primarily relate to efficiency gains. Moreover, building on IT security literature the perceived risk of security threats as another significant attitudinal component in intention formation is hypothesised to considerably inhibit the willingness to adopt smart wearable devices. The effect of trust on consumer's usage intention is in turn supposed to be mediated by security risk perceptions and to thus indirectly influence the criterion variable. Likewise, the pervasiveness construct acts additionally as an upstream model parameter of usefulness perceptions. In addition, personal involvement with the product category of interest is also proposed to be positively associated with the adoption decision. Thereby, drawing on the 3M model intrapsychic predispositions are assumed to determine the level of personal involvement with the research object and to thus find expression in behavioural patterns, as well. Further on, personal innovativeness and wearable computing experience are *a priori* proposed to exert a moderating effect on the dependency structures of the value perception-related belief constructs.

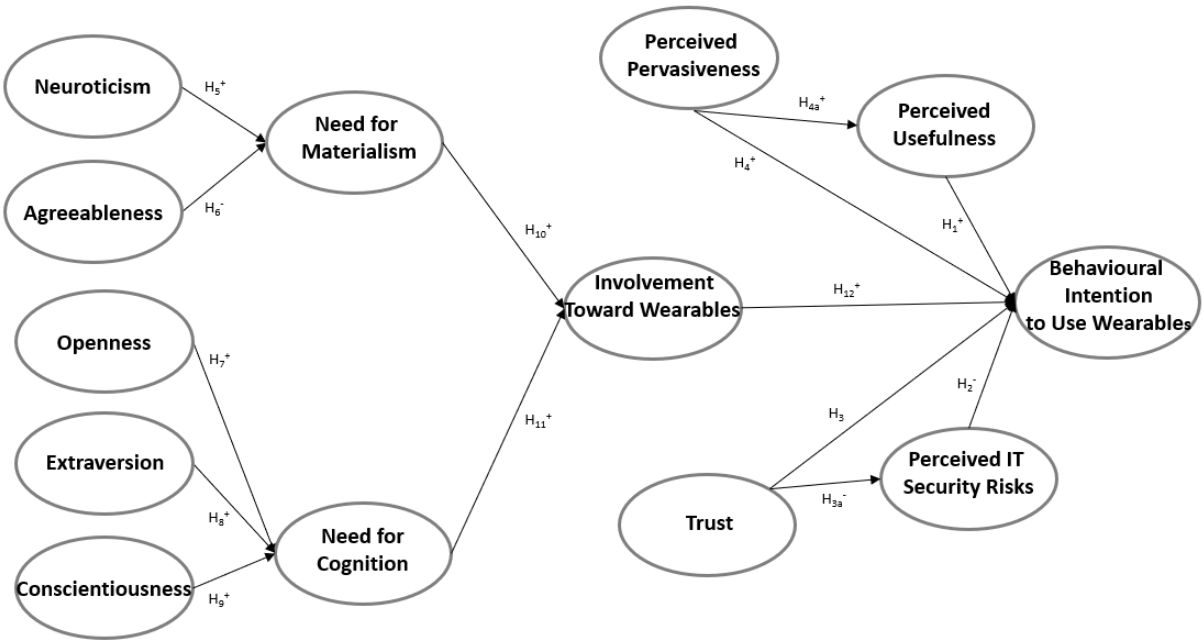

Figure 5.5: System of hypotheses of the overall Wearable TAM to explain the adoption of wearables

Due to the integration of multiple research streams including IT security and personality research, the explanatory power of the proposed cause and effect model can be considered as fairly high. As argued before, the identified hypothetical constructs and model correlations clearly show commensurability: The convergent concepts of the different streams of literature and their common cognitive interest of adoption behaviour provide a connecting

factor in the sense of complementary theoretical explanations. Each research perspective focusses on different behavioural aspects of the same knowledge object. This integrative approach increases the specificity of the generic source model, so that a higher significance of the hypothesised causal relationships may be attained. For validation purposes, a combined analysis of the qualitative study results and the findings from literature research was performed. All formulated research hypotheses are summarised in Table 5.1.

LABEL	HYPOTHESIS
H_1	Increased consumer's perception of the usefulness of wearable computing will result in an increase in the intention to use a wearable computing device.
H_2	Decreased consumer's perception of the security risk of wearable computing will result in an increase in the intention to use a wearable computing device.
H_3	Increased consumer's perception of trust in wearable computing will result in an increase in the intention to use a wearable computing device.
H_{3A}	The relationship between the level of trust towards wearable computing and the intention to use wearables is mediated by perceived security risk.
H_4	Increased consumer's perception of the pervasiveness of wearable computing devices will result in an increase in the intention to use a wearable computing device.
H_{4A}	The relationship between the level of consumer's perception of the pervasiveness of wearable computing and the intention to use wearables is mediated by perceived usefulness.
H_5	Increased consumer's level of neuroticism will result in an increase in consumer materialism.
H_6	Decreased consumer's level of agreeableness will result in an increase in consumer materialism.
H_7	Increased consumer's level of openness to experience will result in an increase in the need for cognition.
H_8	Increased consumer's level of extraversion will result in an increase in the need for cognition.
H_9	Increased consumer's level of conscientiousness will result in an increase in the need for cognition.
H_{10}	Increased consumer's level of materialism will result in an increase in affective involvement.
H_{11}	Increased consumer's need for cognition will result in an increase in affective involvement.
H_{12}	Increased consumer's affective involvement will result in an increase in the intention to use a wearable computing device.

LABEL	HYPOTHESIS
H_{M1}	The relationship between the perceived usefulness of wearable computing and the behavioural intention to adopt is positively moderated by the product category-related innovativeness.
H_{M2}	The relationship between the perceived security risk of wearable computing and the behavioural intention to adopt is negatively moderated by the product category-related innovativeness.
H_{M3}	The relationship between the perceived usefulness of wearable computing and the behavioural intention to adopt is positively moderated by the level of personal experience.
H_{M4}	The relationship between the perception of the security risk of wearable computing and the behavioural intention to adopt is negatively moderated by the level of personal experience.

Table 5.1: Summary of hypotheses

5.5 Chapter Conclusions

So far, in compliance with the research aims stated initially, this study developed an integrated causal model on the individual intention formation towards the use of wearable technologies. It thereby answers the research question on how to contextualise and transfer the relevant acceptance factors into an exploratory acceptance model. In sum, 12 causal and 4 moderating hypotheses were derived from theory. These theoretic assertions interconnect the qualitatively identified constructs of the 'Wearable TAM' to a new nomological network, so as to holistically explain acceptance behaviour towards wearables. In order to increase validity and comparability of the proposed hypotheses, model development was based on a review of related theories and frameworks in marketing and Information Systems research. Beside the integration of several salient technology beliefs which may possess great explanatory capacity in a wearable computing context, the well-established TAM has been extended by a dispositional perspective. Based on the 3M model, the theoretical framework developed proposes a hierarchical model of personality-related predictors of adoption behaviour, which is fully mediated by the involvement towards wearables. Overall, the synthesised research model can be considered a *partial model* due to its main focus on constructs that are particularly relevant for the specificities of the research context at hand (Gross, 2014, p. 119). This ensures a relatively high degree of both explanatory power and efficiency within the investigational domain of the present study. Ultimately, the pursued in-depth understanding of the causal mechanisms involved in the formation of acceptance decisions can be translated into measures of product and communication policy that appeal to consumers.

However, it should be stated that the postulated nomological net still lacks empiricism in terms of a quantitative validation. Thus, the identified latent constructs ought to be operationalised through manifest (i.e. directly observable and thus quantifiable) counterweights. As a consequence, appropriate measurement instruments should be specified that enable an empirical analysis of the theorised overall correlation structure. Therefore, in chapter 6.4 suitable indicators (in the sense of manifest responses) are selected that capture the constructs in that they empirically correlate with them.

6 Quantitative Approach

What we observe is not nature itself, but nature
exposed to our method of questioning.
Werner Heisenberg

This chapter outlines the quantitative study of present research. At first, the employed research design is discussed, which includes also a detailed examination of the chosen data analysis technique. Next, measurement instruments are developed in order to operationalise the formulated hypotheses and to establish a basis for questionnaire development.

6.1 Quantitative Research Methodology

Since every research design is implicitly shaped by a philosophical worldview (i.e. epistemological and ontological paradigm), it is important to state clearly which school of thought is taken for the purpose of a given research project. It should also be clarified at which points this worldview interacts with the practice of research in terms of a guiding paradigmatic underpinning (Creswell, 2013, p. 6). As the present research is approached through the philosophical lenses of the post-positivist tradition (see chapter 4.1), it is assumed that scientific theories can never be proven true conclusively and thus remain tentative in nature (Popper, 1959, p. 280). According to the **principle of falsifiability**, hypotheses can only be provisionally accepted if they withstand continuous attempts to falsify them (Scotland, 2012, p. 10). Thus, evaluating the truth-value of hypotheses becomes epistemologically a deductive procedure that focusses on the refutation of the pertaining null hypotheses per empirical evidence of a nonzero difference or correlation of the variables that comprise the research questions (DeLuca, et al., 2008, p. 57). The post-positivist stance therefore challenges the traditional positivistic notion of a total verification of hypotheses. Post-positivism rather seeks corroboration or gradual empirical support for scientific claims by quantitatively testing theoretical propositions in larger, well-defined social contexts. Since this worldview reflects a deterministic philosophy in which reductively deducible causes *probably* determine specific outcomes (Creswell, 2013, p. 7), scientific research should be directed towards the nomothetic (i.e. general, lawful) goal of developing *explanans* (i.e. testable hypotheses) that are reliable and both internally and externally valid to the greatest possible extent within a specified domain (Amaratunga, et al., 2002, p. 22; Daly, 2007, p. 31; Harris, 2012, p. 32).

Post-positivism contends that the sustained success of a scientific proposition "gives us reason to believe that 'something like' the entities contained in the theories actually exist" (Hunt, 1990, p. 10). As opposed to strict falsificationsim, the post-positivism ontology motivates modesty regarding falsification and verification alike (Miller & Tsang, 2011, p. 140). In this sense, Carnap (1945, p. 531) refers to the metrical concept of the *degree of confirmation*, whereby the binary logic of a theory to be either 'true' or 'false' is superseded by a multivalued logic adhering to a continuous scale of probability. In other words, judgments concerning theoretical proposition are not passed on the bipolar predicate 'false-true', but rather on a unipolar 'false-not false' spectrum accounting for the probabilistic nature of claims. In the case of several competing theories, Bhaskar, who originally developed

the post-positivists' ontological domain of critical realism, recommends to prefer those scientific propositions that possess the greatest **explanatory power** (1989, p.73). Complementarily, Lakatos (1970, p. 178) provides the characteristic **simplicity** as a normative criterion for determining the adequacy of a theory. As stated before, the Wearable TAM accordingly links multiple streams of literature to arrive at an explanatory efficient and simultaneously powerful system of hypotheses in a wearable computing adoption context.

Summarising the above, the post-positivist philosophy stretches the percept of positivism by replacing absolute certainty and objectivity with the tentativeness of falsifiable knowledge and inter-subjectivity (Daly, 2007, p. 30; Riazi, 2016, p. 243; Plack, 2005, p. 227). In order to reduce inherent biases of any methodological technique, the focal belief system suggests to converge upon conceivable objective truths by employing *critical multiplicism* or triangulation in its most comprehensive sense (Plack, 2005, p. 227). Thus, given that total objectivity may never be attained entirely, researchers should triangulate across multiple methodologies and sources of information (Guba & Lincoln, 1994, p. 110; Planing, 2014, p. 83; see also chapter 4.1.1). Conforming to this central tenet of post-positivism the quantitative study employs a confirmatory approach that is built upon the findings of the conceptual and qualitative study applied so far.

Furthermore, conceding that human knowledge is always imperfect and fallible, the pursuit of rigor and control in research design foregrounds as a prime value for post-positivists to explain social realities (Daly, 2007). Hence, knowledge acquisition is centred on a search for neutrality, care in theorising and critical reflections upon empirical results. In order to achieve this objectives, a scientific method (i.e. a set of standardised techniques for acquiring scientific knowledge) has to be used throughout the validation of a proposed conceptual framework to meet the four essential empirical criteria (Bhattacherjee, 2012, p. 5): *replicability* (a study should be independently replicable), *precision* (theoretical concepts should be measurable), *falsifiability* (theories can be evaluated and disproven), and *parsimony* (the most parsimonious theories has to be favoured). The confirmatory study should thus rely on a scientific research process including (Bhattacherjee, 2012, p. 20):

- A *representative* sample of the target population
- A *valid* operationalisation of the identified abstract hypothetical constructs including clear definitions of the concepts at both abstract (conceptual) and empirical levels.
- *Appropriate* statistical methods for comprehensively analysing the empirical results.

On that account, by taking a quantitative approach the validation phase of this thesis was conducted through a multi-stage process of appropriate construct operationalisation, sampling, and analysis. In advance of the development of suitable measurement instruments, the following subsection gives considerations on how the conceptualised behavioural model on wearable technology acceptance can be evaluated empirically using a scientific method. Afterwards, particular focus is put on scale construction and subsequently on available methods for data collection and data analysis.

6.2 Multivariate Data Analysis Methodology

Generally, theoretical associations ought to be transferred into a set of structural relationships, so as to formalise the proposed theoretical model and to allow for empirical evaluation of propositions (Hair, et al., 2017 p. 6). Hence,

this chapter is guided by the central research question on how the generated system of hypotheses should be formally explicated and how the proposed framework should be tested for its quality. After a comprehensive introduction and justification of the chosen data analysis technique, the main quality criteria for empirically assessing the propositions are thus presented in this subchapter.

6.2.1 Structural Equation Modeling

As the hypothesised research model consists of several interdependent variables, which simultaneously serve as both predictor and criterion variables (i.e. intervening variables), traditional multiple regression approaches fall too short (Hair, et al., 2010, p. 708). Further requirements arise from the theoretical nature of the incorporated latent variables, i.e. the *a priori* conceptualised constructs have to be operationalised by means of corresponding measurement models in order to become empirically accessible. In addition, considering the basic assumption in psychometric theory, the analysis should account for error terms that are inherent in all measurement (Hair, et al., 2016). Thus, in order to be capable of validating the proposed complex dependency structures adequately against empirical data (i.e. to perform a confirmatory analysis), **structural equation modeling** (SEM) appears to be a promising multivariate technique. The concept of SEM refers to a second-generation family of multivariate statistical methods that seeks to estimate interrelated dependence relationships among multiple theoretical constructs (Hair, et al., 2010, p. 708). SEM-based methods go beyond first-generation regression-based techniques (e.g. principal component analysis, discriminant analysis, etc.) in that they combine multiple regression and factor analytic models. Consequently, this hybrid coupling of both traditional econometric and psychometric perspectives enables researchers to systematically conduct path analytic modelling with multiple layers of latent constructs at once (Chin, 1998a, p. 295; Gefen, et al., 2000, p. 3 f.).

From a methodological view, SEM techniques express the structure of predictive or causal interrelationships of a theory in a series of separate, but interdependent, multiple regression-like structural equations (Hair, et al., 2010, p. 709). Therefore, SEM-based path models can also be referred to as multi-equation systems. Typically, structural path modelling incorporates two major submodels: the structural model (also termed the *inner model*), which depicts the system of hypotheses that interrelates the latent variables, and the measurement model (i.e. *outer model*), which accounts for the relationships between the latent variables and their measures (Haenlein & Kaplan, 2004, p. 286). This distinction mirrors the two-language-theory by Carnap (1966), who distinguishes between a theoretical language (i.e. level of hypothesised theoretical constructs) and an empirical level that reflects the level of observable or quantifiable measurement variables.

Notably, since correlation does not necessarily imply causation, SEM analysis results can never provide conclusive evidence for causation (see also the influential work on path analysis by Wright, 1921). Exogenous variables cannot be controlled experimentally in SEM research, what might give rise to spurious correlations due to multicollinearity effects between the predictor constructs and possible confounding third variables (Hair, et al., 2010, p. 717). Assuming an underlying mechanism that leads to a theoretical covariance structure essentially captured by the sought model, the parameters estimated by SEM suggest primarily *inference relationships* between the hypothesised constructs and, thereby, provide merely cues to *causal relationships* (Iriondo, et al., 2003 p. 368; Schumacker, et al., 2009 p. 48). Consequently, empirical correlation between latent factors serves in terms of a

sine qua non condition, which alone is yet not sufficient for validly inferring causation from observed relationships. In other words, rather than deriving causal claims from SEM results, researchers should build their structural models upon their causal assumptions (Bollen & Pearl, 2013, p. 312). It becomes clear therefrom that every causal hypothesis has to draw upon strong *a priori* or experimental grounds derived from substantive theory, logical considerations or practical experience (Hair, et al., 2016 p. 37). In this context, Bullock and colleagues point out that no statistical routine could *per se* establish true causation in nonexperimental data (1994, p. 257). Rather, the causal potential should be determined by the degree of control and validity of both the apriorically developed structural model and the measurement model.

Basically, SEM analysis is a framework that demands a multi-stage process following a hypothetico-deductive fashion: The procedure starts with a theory-based specification of the structural model that interconnects the relevant theoretical constructs (Schumacker, et al., 2009 p. 55; Hair, et al., 2016 p. 37). In this context, it should be reiterated that only well-founded theories can lend credibility and validity to empirical findings (Bollen, 2011, p. 361). That is, theory and logic should ultimately ground the temporal sequence of the derived mental states intervening between external stimuli and observable behaviours. For the present research, the structural model that synthesises the hypothesised causal relationships into an integrative acceptance model was already conceptualised in chapter 5.

Afterwards, appropriate measurement models have to be developed in order to operationalise these theory-relevant constructs correspondingly. In logical empiricism, the canonical form of the structure of scientific theories provides that theoretical constructs have to be related to implied empirical laws or concepts by means of *correspondence rules* (Bagozzi, 1984, p. 17). Based on Carnap's premise that theoretical and empirical terms represent end points of a continuum (1966, p. 225 f.), correspondence rules help to convert concepts at empirical level into observable manifestations. By virtue of adequate operational definitions and diligently specified measurement instructions, they provide empirical significance to theoretical terms (Bagozzi, 1984, p. 17; Haenlein & Kaplan, 2004, p. 286). In line with this reasoning, the existence of a theoretical concept implies the occurrence of at least one observable event that is semantically tied to that abstract concept (Bagozzi & Phillips, 1982, p. 466). Thus, in order to integrate theory with rigorous methodology, the empiric values of the hypothesised theoretical constructs should be determined with the aid of apriorically derived manifest measures (alternately termed as indicators) that are quantifiable (i.e. inter-subjectively ascertainable) via empirical means such as self-reports, interviews, or observation (Petter, et al., 2007, p. 624 f.). The operationalisation of the latent exogenous and endogenous variables identified in the present study is discussed in chapter 6.3.

In order to advance scientific knowledge and to avoid a confusing array of different construct definitions, psychometric literature suggests to select empirically established measurement approaches validated in prior studies or published in handbook scales (Jacoby, 1978, p. 91; Churchill, 1979, p. 67). Generally, for the sake of content validity it is of significance to distinguish between **formative** and **reflective** measurement perspectives (Blalock, 1964, p. 163; Bollen, 2011, p. 360; Fornell & Bookstein, 1982, p. 441). For clarification, the path diagram of each measurement model is illustrated in Figure 6.1. Both approaches assume an opposite direction of causality between the latent constructs and their indicators (Jarvis, et al., 2003, p. 200).

Following a regression analytical approach, the formative perspective interprets indicators as distinct causes of their underlying composite construct. Formative or composite indicators jointly define the domain of content that constitutes the focal construct. Therefore, they do not have to be intercorrelated by necessity as would be the case if they were conceptually interwoven (Diamantopoulos & Siguaw, 2006, p. 267). Accordingly, in measurement literature the operationalisation of linear composite variables is commonly also referred to as index construction, where the battery of indicators fully produces its respective index or construct with an R^2-value of ideally 1.0 (Diamantopoulos, et al., 2001 p. 271). Based on the assumption that $COV(x_i,\zeta_i)$ equals zero for all i, the theoretical construct can be presented mathematically as follows (Bollen & Lennox, 1991, p. 306):

$$\eta = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_n x_n + \zeta \tag{6.1}$$

where η denotes the deviation score of the construct, γ represents the weight, x depicts the respective formative indicator and ζ is the disturbance term of the formatively measured construct, capturing all further possible causes that are not incorporated in the model. Notably, if the residual variance at construct level would correlate with the idiosyncratic error terms of the indicators, this would necessarily imply an incomplete model specification (Diamantopoulos, 2006, p. 11). Since formative indicators jointly determine the focal construct's meaning, they are neither interchangeable nor eliminable, as is true with reflective indicators (Hair, et al., 2016 p. 47). Otherwise, if an indicator would be omitted, this would alter the construct's nature and, thus, would definitionally lead to another conceptual domain.

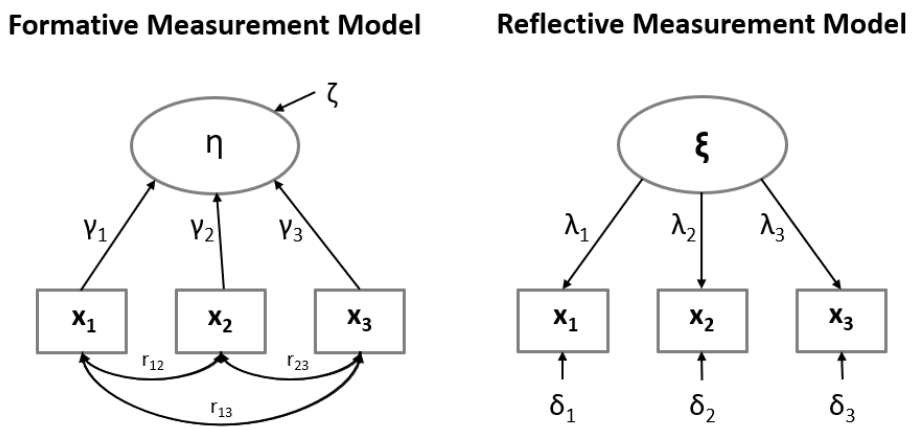

Figure 6.1: Formative versus reflective measurement models (Based on Bollen & Lennox, 1991, p. 306)

On the contrary, according to the reflective measurement philosophy, the measures that represent the observed variances are all caused by the same underlying construct (Bollen, 2011, p. 360). This means that variation in the latent factor is reflected by similar directional changes in its dependent *effect indicators*. Due to their conceptual unity, reflective indicators should be highly correlated with one another to provide internal consistency (Hair, et al., 2016 p. 47). The subsequent equation represents the correspondence rule in the case of an endogenously conceptualised, reflective construct (Bollen & Lennox, 1991, p. 305):

$$x_i = \lambda_i \eta + \varepsilon_i \tag{6.2}$$

where the reflective indicator x is a function of its associated latent variable η with the factor loading vector λ and the vector of measurement errors ε. The reflective indicators can be understood in the sense of manifestations or imperfect reflections of their latent phenomenon, randomly drawn from a universe of equally suitable measures (Albers, 2010, p. 414; MacKenzie, et al., 2011, p. 295). Since they indicate their principal factor latent construct's score in terms of equally valid effects, they are – contrarily to formative indicators – substitutable and omittable, as long as their construct yields sufficient reliability (see chapter 6.2 on the relationship between construct reliability and scale development). In technical terms, a perfect measurement without systematic and random errors would ultimately result in fully correlated reflective indicators.

The specification of a measurement model depends primarily on the conceptualisation of the construct (i.e. the predefined content domain of the latent variable) and the study objective (Hair, et al., 2016 p. 50). Albers (2010, p. 410) argues that in success factor studies in the area of organisational and marketing effectiveness, especially multifaceted managerial concepts that hold promise for explaining (non)response behaviour represent a major concern. Consequently, complex pre-purchase variables should be analysed in terms of the relative importance of their causes which ultimately drive the success. The ability to analyse the individual effect of each facet of a theoretical construct renders particularly important for usefulness perceptions, since the different beliefs that underly a utility judgment do not necessarily covary or describe the same quintessential content domain (Petter, et al., 2007 p. 635). Given the scope of the present study, it appears therefore worthwhile to investigate the single causes of perceived usefulness of wearable computing as a main reason for usage intention.

From a conceptual standpoint, the choice between reflective and formative measurement models substantially affects estimation procedures and subsequent model interpretation (Fornell & Bookstein, 1982, p. 441). Misspecifications of the outer structures may increase the potential for both Type I error (declaring a path significant when it is really nonsignificant) and Type II error rates (declaring a path nonsignificant when it is really significant), because structural parameters could be conceivably over- or underestimated (Jarvis, et al., 2003, p. 207; Petter, et al., 2007, p. 624). Various authors in the field have already criticised the predominate use of reflective measurement conceptions. This bias may be traced back to classical test theory and a general tendency in research practice to neglect the nature of outer structures synthesised by an inner model (Edwards, et al., 2000 p. 156; Diamantopoulos, et al., 2001 p. 269; Petter, et al., 2007 p. 624).

Latent variable measurement specification ultimately dictates the choice of construct validation techniques, since reflective relationships are primarily subject to both factor analysis models and reliability tests, whereas formative constructs are typically estimated via multiple regression (Edwards & Bagozzi, 2000, p. 155 f.). To avoid measurement model specification errors, researchers should theoretically determine the causal direction of the relationships between constructs and measures implied by the pertaining conceptual definition. The question of causality can be answered by considering whether a) the indicators are descriptive characteristics (formative) or rather manifestations (reflective) of the latent construct, or, b) to what extent covariation among indicators is expected to cause changes in the construct, et vice versa (Jarvis, et al., 2003, p. 203; Edwards & Bagozzi, 2000, p. 156 ff.). Jarvis and colleagues have summarised further criteria to guide decision on the appropriate measurement model (Jarvis, et al., 2003, p. 203). These criteria include both the afore-mentioned interchangeability and intercorrelatedness of indicators inherent to the reflective perspective as well as the conceptual allocation of the

focal construct's indicators within the postulated nomological network. This means that reflective measurement variables should always have the same antecedents and consequences, given that they are semantically redundant and possess a 'common cause'.

After having specified and validated all measurement models provided by the proposed structural theory, the next step in SEM analysis is to format the system of hypotheses graphically by a path diagram, which shows how the theoretical constructs relate to each other (Haenlein & Kaplan, 2004, p. 286). In accordance with the canonical notation system provided by Jöreskog and Sörbom (1996), Figure 6.2 illustrates such a formalised structural model encompassing four outer models (i.e. latent variables). The latent endogenous variables are represented by η (eta), whereas the predictive exogenous variables are depicted by ξ (xi). As per convention, the random disturbance terms of the endogenous variables are marked with ζ (zeta), the residuals of the indicators of the exogenous variables are labelled with δ (delta), and the measurement errors of the endogenous constructs' indicators are denoted with ε (epsilon). The causal paths are portrayed by single-headed (i.e. unidirectional) arrows, which signify the postulated direction of effect. Structural path coefficients of relationships between exogenous and endogenous constructs are expressed by γ (gamma), whilst the path coefficients in-between endogenous variables are represented by β (beta).

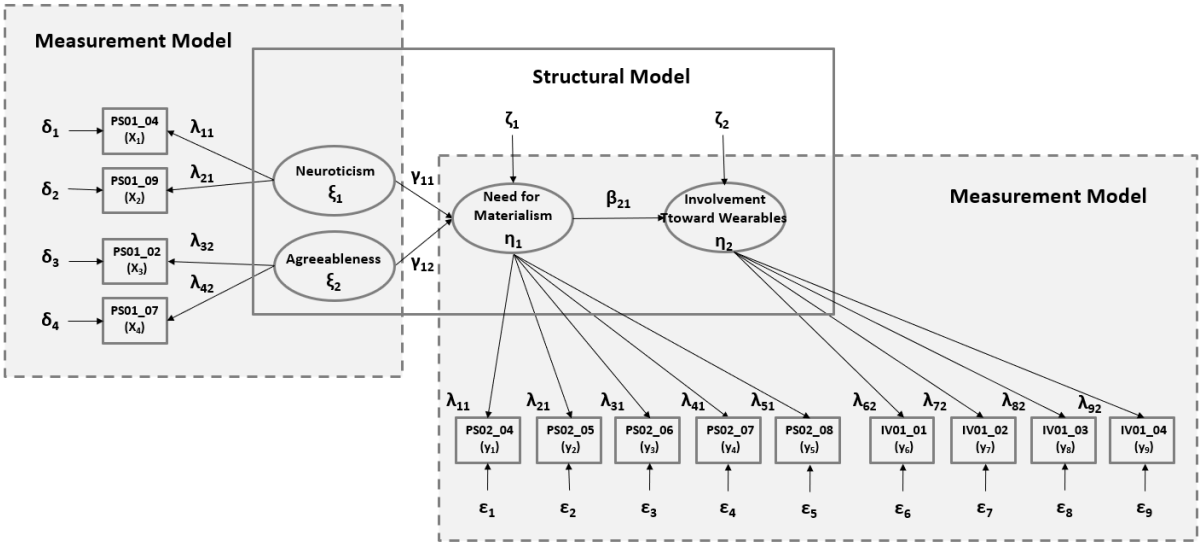

Figure 6.2: Partially-recursive path diagram consisting of two measurement models and an inner structural model (Notation based on Jöreskog and Sörbom, 1996, p. 6)

Following the above construction rules for recursive path diagrams, the linear structural and measurement model equations can be derived (Jöreskog & Sörbom, 1996, p. 5 ff.). Specific to the structural equation system is, in particular, that each dependent variable of the inner and outer models is described by a corresponding individual equation. For instance, the above endogenous latent variable η_2 in the theoretical path diagram can be represented as follows: $\eta_2 = \beta_{21}\ \eta_1 + \zeta_2$. By transforming a path diagram into matrix algebra, the regression function of the structural model can be written as:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{6.3}$$

given that B und Γ are coefficient matrices of the endogenous and exogenous variables, respectively. Furthermore, from equation 6.2, where the indicators are expressed as a function of their pertaining latent variable, it follows that (Henseler, et al., 2009 p. 285):

$$y = \Lambda_y \eta + \varepsilon \tag{6.4}$$

where Λ_y denotes the loading (pattern) coefficients of the endogenous measurement models. Acknowledging that each indicator represents an error-afflicated measurement, the corresponding regression residual is quantified by ε. Analogously, the same applies for the vector of the exogenous latent variable:

$$x = \Lambda_x \xi + \delta \tag{6.5}$$

where the factor loadings of the exogenous measurement models are denoted by Λ_x, and the error variance component by δ.

The herein introduced perspective considers composite variables to be hypothetical proxies for latent concepts, which describe and assign significance to real phenomena in social collectives that might be of scientific discourse. Remarkably, the understanding of constructs in the sense of theoretical surrogates for objectively real phenomena represents a critical realist paradigm: It is recognised that these phenomena cannot be observed directly or with absolute accuracy due to measurement error and imperfect epistemological lenses (Edwards & Bagozzi, 2000, p. 157). Nevertheless, by demonstrating ongoing usefulness, some constructs may contribute to the body of knowledge and hence might aid managerial decision-making.

The next stage in structural equation modeling is to estimate the formulated regression paths (Hair, et al., 2016 p. 30). To this end, there are two main approaches: the covariance-based and the variance-based Partial Least Squares (PLS) approach (Chin, 1998a, p. 297). Even though both methods apply to the same class of models (i.e. structural equation models including unobservable variables and measurement error), they differ markedly in regard to the epistemic relationship between data and theory (i.e. their parameter estimation mechanism), the properties of the empirical data, and the objective of analysis (Chin, 1995, p. 316). Therefore, the next section contrasts the main distinguishing statistical features and assumptions of these approaches.

6.2.2 The Partial Least Squares Approach

The **covariance-based approach** (CB-SEM) is anchored on the fundamental theorem of factor analysis. It holds that each measurement variable can be described as a linear combination of its hypothetical factors and that the correlation matrix of the collected data can be fully reproduced using the matrix of factor loadings and the correlations between the factors (Meister, 2012, p. 187). Correspondingly, based on confirmatory factor analysis CB-SEM attempts to reproduce the covariance matrix of the manifest variables in such a manner that the discrepancies between the parameter matrices of the predicted theoretical model (e.g. Λy, Λx, B, Γ, Φ, Θε und Θδ) and the sample covariances (e.g. of the manifest variables $x_1,\ldots,x_6$ and $y_1,\ldots,y_6$) are minimised (Chin & Newsted, 1999, p. 309). The CB-SEM algorithm therefore seeks to explain the covariances of all the indicators. There are different estimation algorithms for minimising the fitting function between the population parameters that underlie the empirical matrix and the model-implied covariance matrix, e.g. the maximum likelihood (ML), the generalized

least squares (GLS), and the weighted least squares (WLS) method (Olsson, et al., 2000, p. 557; Savalei and Rhemtulla, 2017, p. 8). Because of their computational simplicity and statistical accuracy, especially the ML and GLS estimators are the most commonly applied normal-theory methods heretofore (Fischer, 2010 S. 167; Singer, 2015). Since these full-information estimation methods provide inference statistical criteria for holistically assessing the consistency of the reproduced variance-covariance-matrix that mirrors the empirically measured *structural relations* of all measurement variables, they are particularly appropriate for theory testing, given that substantive theoretical knowledge already exists (Barroso, et al., 2010, p. 430).

As a multivariate technique that follows the common factor analytic approach, where p manifest measures are conceived as both linear combinations of hypothetical factors and as decomposable into p factor variances and p random error variances (cf. equation 6.4 and 6.5), CB-SEM models attempt to capture only those proportion of variance that is caused by the latent factor (Chin, 1995, p. 315; McArdle, 1990, p. 81). Hence, correlation between indicators is causally attributable to the pertaining latent factor in the sense of the reflective measurement philosophy. This methodology implies the genuine problem with covariance-based model identification, according to which the sample covariance matrix has to include at least as many structural equations as the number of model parameters to be estimated (Reinartz, et al., 2009, p. 332 ff.). Since formative constructs can be thought of as linear transformations of their respective indicators into one composite proxy variable, formative measurement models can only be expressed by means of just one single equation, though. Therefore, CB-SEM-based estimators are methodologically less suitable for rendering formative measurement approaches (Hair, et al., 2011, p. 143). A technical side issue that has to be considered in this context is the *factor indeterminacy* problem that results from the inability of covariance fitting approaches to estimate unique latent factor scores: Because an infinite number of possible factor scores may equally fit the theoretical model, correlations between the latent variate and any variable outside the factor structure are likewise indeterminate. For this reason, CB-SEM is highly inappropriate for predictive applications and theory development (Hair, et al., 2016 p. 17).

Another restriction of traditional CB-SEM that arises from the underlying multivariate analysis perspective refers to the assumption of multivariate normally distributed data, what is, however, rarely met in practice (Reinartz, et al., 2009, p. 12 f.). Moreover, because parametric estimators require the population covariance matrix to be positive-definite (i.e. the implied matrix must not contain correlation coefficients greater than 1.0), covariance structure analysis demands both a minimum sample size and a minimum number of indicators per construct (ibid., Schumacker & Lomax, 2009, p. 40). In this regard, some studies indicate that under certain modeling conditions even 5,000 cases do not suffice (Hu, et al., 1992, p. 356), whereas other authors recommend a ratio of 20 subjects per item as a rule of thumb to generate results with error rates above an alpha-level of .05 (Osborne & Costello, 2005, p. 7). What is more, in literature the general consensus is to employ at least three to four indicators per latent factor to assure more reliable parameter estimates (Reinartz, et al., 2009, p. 12). Assuming 13 conceptual variables as is the case in the present study, this would result in a minimum sample size of 780 observations.

Due to these restrictions on model and sampling characteristics, **partial least squares** (PLS) path modeling has gained considerable momentum in nonexperimental research over the last decade (Dijkstra & Henseler, 2015a, p. 10). The **variance-based PLS** approach that was originally developed by Wold is primarily intended for "[…] causal-predictive analysis in situations of high complexity but low theoretical information" (Wold, 1982, p. 270).

Instead of reproducing parametrically the population covariance matrix, the PLS-SEM framework aims at minimising the residual variance of the endogenous latent variables. By increasing the explained variance of all dependent variables through a series of **ordinary least squares** (OLS) regression-based analyses, PLS strives to reproduce the case values of the raw data. Basically, the PLS-SEM optimisation algorithm follows a two-tier approach, commencing with an iterative four-stage estimation procedure of the latent factor scores (Hair, et al., 2011, p. 142):

(1) In the first step the outer proxies (i.e. tentative latent variable scores) are estimated as linear combinations of their standardised manifest predictors. Initially, when no weights are available, PLS utilises any "[…] arbitrary non-trivial linear combination of indicators […] as an outer proxy of a latent variable" (Henseler, 2010, p. 111). In the following iterations, construct values are calculated based on the coefficients of the paths between the latent constructs and their respective indicators estimated in step 4.

(2) In the second step PLS computes the inner weights that approximate the strength of the structural model relationships. For this purpose, there are three primary inner approximation weighting schemes available, including the centroid scheme, which uses the sign of the correlation between two adjacent variables, the factor weighting scheme that uses the bivariate correlations, and the path weighting scheme, which draws on regression coefficients in the case of dependent variables and – similarly to the factor weighting scheme – correlation coefficients in the case of independent variables. Because only the path weighing scheme thus accounts for the direction of causality, this scheme is recommended in methodologically oriented articles (Hair, et al., 2011, p. 142).

(3) Based on the scores of the latent constructs obtained in step 1 and the afore-determined inner weights for the structural relationships from step 2, in a third step new constructs' inner scores are computed as linear combinations of their nomologically contiguous latent variables.

(4) Finally, based on the scores obtained from the previous step the outer weight coefficients (i.e. the coefficients in the measurement models) are estimated. In the case of reflective indicators, a simple regression of each manifest variable on the construct's estimated inner proxy (outer loading) is applied. Contrarily, in the case of formative indicators an OLS regression of the latent variables' inner score on its indicator block is calculated. The resulting outer weight coefficients are subsequently used in step 1.

The PLS optimisation algorithm iterates over these steps until the sum of absolute changes of the auxiliary weights converge to a predefined threshold value (Chin, 1998a, p. 302). This convergence criterion for aborting the PLS routine that oscillates back and forth between the inner and outer approximation of the constructed indices is commonly set to 10^{-7} (Hair, et al., 2016, p. 91 f.). As both the inner and the outer estimators are based on a least squares approach, each step of the algorithm successively minimises the unexplained variance, wherefore PLS is considered as being "coherent in a predictive sense" (Chin, 1998a, p. 303).

Once the construct scores are calculated, the factor loadings of the outer models as well as the path coefficients of the structural model are to be estimated in stage two of the PLS estimation algorithm. Drawing on PLS's econometric background with its traditional path analytic methodology, each endogenous latent variable score is thereby regressed on its latent predictor variable scores via simple OLS regression (Henseler, 2010, p. 111).

Finally, mean values and location parameters for the distribution of each latent construct can be determined (Chin, 1998a, p. 302).

Owing to the partial nature of PLS (i.e. the relational structures of the overall model are estimated partially), the sample size requirements are much smaller compared to those of CB-SEM (Chin, 2010, p. 661). An often-cited heuristic suggests that the sample size should be at least ten times larger than a) the largest number of formative indicators for measuring a single index, or, b) the number of inner paths directed to the theoretical construct with the most structural relations (Barclay, et al., 1995, p. 285 ff.). Empirical research could show that in technical terms PLS is even able to provide interpretable estimates with only 50 cases (Chin & Newsted, 1999). Nonetheless, even though the PLS approach outperforms ML-based CB-SEM in terms of parameter convergence behaviour in small samples with $n \leq 200$ observations (Boomsma & Hoogland, 2001, p. 139 ff.), as with other multivariate data analysis techniques, statistical power and effect sizes should be taken into account to prevent Type II errors and to ensure generalisability of results (Reinartz, et al., 2009, p. 13; Henseler, et al., 2014, p. 198; Goodhue, et al., 2012, p. 983). In addition, because latent variable scores represent aggregates of manifest measures including their inherent residual variance, path model relationships tend to be systematically underestimated, whereas outer model parameters are typically overestimated (Chin, 2010, p. 663). This inconsistency in parameter estimates is mistakenly termed **PLS-SEM bias**, which neglects the techniques' differing purpose and its composite-based character. Inherently, PLS treats theoretical constructs as exact weighted composites of their pertaining indicator blocks (Rigdon, 2014, p. 162). Simulation studies have demonstrated that if sample and measurement model characteristics meet the minimum recommended standards in terms of both sample size and number of manifest measures, then the parameters estimated approximate the true population parameter values (Jakobowicz, 2006, p. 727; Chin, et al., 2003). This property of variance-based estimators is commonly referred to as *consistency at large* (Schneeweiss, 1990, p. 38; Wold, 1982, p. 25; Lohmöller, 2013, p. 213 ff.). As a remedy for PLS-SEM's lack of consistency, Dijkstra and Henseler propose in (2015b, p. 297 ff.) the **consistent PLS** (PLSc) approach, which produces disattenuated correlations by dividing the correlation of reflective latent variables by the geometric mean of the constructs' reliabilities. In PLSc, regression coefficients between formative constructs remain unchanged. Yet, Hair and colleagues (2017, p. 303) emphasise that in complex path models collinearity among constructs as well as low levels of construct reliability have strong adverse effects on PLSc results.

Aside from the relative efficiency of PLS being a partial-information approach, nonparametric techniques do not require multivariate normally distributed indicators (Fornell & Bookstein, 1982, p. 442). Because of their comparably soft distributional assumptions that comply with the *central limit theorem* (see chapter 6.2.1), variance-based techniques work well with non-metric scales and dichotomous variables (Hair, et al., 2016 p. 27). Furthermore, as latent construct scores are determinate under a *principal component analysis* (PCA) perspective, PLS-SEM can easily handle formative measurement models without any identification problems, which regularly occur in factor-based CB-SEM settings (Chin, 1998a, p. 303). Another often cited benefit of PLS refers to its capability of managing complex research models with many structural relations, since a limited information approach that estimates successively each subpart of a path model is not restricted by identification issues (Ringle, et al., 2012, p. iv). Consequently, the composite-based PLS algorithm can efficiently handle hierarchical component models as well as both moderating and higher-order interaction effects, what clearly expands its applicability in behavioural and business science disciplines – especially against the backdrop that hypothesised

relationships become increasingly complex in the context of social sciences (Hair, et al., 2011, p. 148; Henseler & Chin, 2010, p. 83; Henseler & Fassott, 2010, p. 713).

However, since PLS parameter estimates focus on a local optimisation of partial model structures, there is no adequate overall goodness-of-fit measure in a CB-SEM sense such as the chi-square ($\chi 2$) statistic (Henseler, et al., 2009 p. 297). Instead, in PLS path modeling the global goodness of model fit is determined by the structural model's predictive capabilities (Hair, et al., 2016 p. 192). More precisely, the assessment of model fit relies on empirical confidence intervals and hypothesis testing procedures such as **jackknifing** and **bootstrapping**, which are outlined in chapter 6.2.4 (Henseler, et al., 2016, p. 9). Yet, the absence of a unique global scalar function to judge the theoretical model's overall quality severely limits the use of variance-based approaches for theory testing and confirming (ibid.). Several relevant authors in the SEM field nevertheless question the meaningfulness of model fit indices in a PLS-SEM context, since PLS does not aim at minimising the distance between observed and model-implied covariance matrices as is the case for theory-oriented CB-SEM (Hair, et al., 2016 p. 194).

6.2.3 Rationale for Choosing PLS

In SEM literature, both the covariance fitting and the variance-based approach to causal modeling are considered to be complementary rather than competitive in that they serve for distinct research contexts and objectives (Henseler, et al., 2009 p. 296). Due to their underlying divergent measurement philosophies (factor-based versus composite-based), they place different requirements on data and model characteristics as discussed above. Accordingly, Hair et al. urge colleagues to align their choice of method with the individual research purpose, data characteristics and model setup (2016, p. 22). Therefore, the following sections briefly discuss the suitability of the PLS approach in the present study context.

The primary research aim of this study is to examine key factors that lead to either acceptance or rejection of wearable computing. This research problem refers to a novel phenomenon for which no comprehensive structural model has been developed so far. In addition, there is still a lack of systematic research on the inclusion of both subjectively perceived IT security risks and personality-related correlates in Information Systems path models. Thus, following an exploratory research strategy this study may benefit more from the predictive capabilities of PLS-SEM than from the parameter accuracy of its common factor-based counterpart (Hair, et al., 2011, p. 147). In particular, the total explained variation in the endogenous constructs is of practical relevance for the present research. In praxeological terms, this study aims at transferring hypothesised cause-effect connections into managerial means-end relations, rather than confirming a strong theoretical model in a well-researched domain.

Furthermore, the hypothesised nomological net incorporates an abstract higher-order construct of security-related technology beliefs, which conforms to the multidimensional conceptualisation of security threats in the pertinent IT literature. Based on a consumer value perspective, the empirical study also integrates an analysis of success factors that are thought to induce technology usefulness perceptions. In the area of marketing effectiveness, drivers of economic target parameters are often deemed to be causative in nature and, hence, require a formative measurement mode (Albers, 2010, p. 419). As stated earlier, CB-SEM can handle formative structures only with limitations in order to ensure model identification, which is why this approach renders problematic for measurement model specification. Beside this, with the level of personal innovativeness and experience there are

two interacting third variables inherent in the research model that moderate the influence of the proposed cognitive beliefs on adoption intention. However, the covariance-based method assumes uncorrelated residual terms, while the error terms of interacting variables are partially correlated with the error terms of the predictor and moderator variables (i.e. interaction effects are calculated as the product of both variables, see section 6.2.6.1). Considering the differing epistemic views of CB-SEM and PLS-SEM, due to its determinate nature the latter technique applies best to the complex interrelations reflected by the developed structural model.

Finally, it has to be noted that especially in disciplines of marketing and management sciences the assumption of normally distributed data is often violated (Ringle, et al., 2012, p. viii). Correspondingly, as can be seen from the analysis of multivariate normality in chapter 7.1.5, this distributional assumption does not hold for the present study since the collected data clearly shows non-zero skewness. Given that the PLS algorithm is quite robust against moderate asymmetric data, again the variance-based SEM approach comes to the fore. Additionally, in view of the structural complexity of the Wearable TAM, the less restrictive sample size requirements of PLS-SEM are also favourable for research economic reasons.

To sum up, the PLS-SEM approach appears to be promising for validating the theoretically derived system of statements. More precisely, this technique allows to efficiently evaluate both the psychometric properties of the constructs identified and the proposed correlative influence of the relevant users' traits and beliefs (Henseler, et al., 2009 p. 277). As a consequence, PLS is well-suited for explaining and predicting consumer behaviour in innovative wearable technology markets. In order to assess the validity and reliability of the partial structures of a theoretical model, there is a series of heuristic evaluation criteria available in PLS-SEM. With regard to the analytic goal of an empirical assessment of the Wearable TAM, the following chapters concentrate on the key criteria for estimating the quality of PLS path models at both construct and structural level.

6.2.4 Assessment of Reflective Measurement Models

Recalling PLS-SEM's relaxed distributional assumptions and the consequent lack of a classical parametric inferential framework, covariance-based model fit measures are not fully transferrable to the PLS context. Rather, the assessment of the quality of a structural equation model focusses on dedicated non-parametric metrics that allow to separately assess the measurement models and the structural model. This biphasic evaluation is critical to PLS path model analysis since the determination of structural parameters and factor scores relies heavily upon the estimation of outer weight relations as implied by the core PLS algorithm in chapter 6.2.2. Hence, taking into consideration that the psychometric quality of conceptual variables crucially characterises the 'goodness' of structural parameter estimates, the diagnostic procedure should commence at construct level.

Essentially, the evaluation of reflective measurement models is based on the empiricist concepts of reliability and validity (Hair, et al., 2016 p. 106 ff.). Whereas the concept of reliability refers to the repeatability of findings and, thus, addresses the level of random measurement errors, the criterion of validity additionally requires measurements that are free from systematic errors. Since an accurately captured content domain of a theoretical concept would inevitably lead to a high level of reproducibility of results, reliability acts as a necessary but not sufficient condition for measurement validity. On the contrary, reliable measurements do not necessarily imply a

semantically complete coverage of the intended construct domain. Thus, a measurement is totally valid if both the random and the systematic error term equals zero (Churchill, 1979, p. 65).

With respect to these operational definitions, various partial first- and second-generation criteria are available for judging the reliability of a measurement model. In classical psychometric theory the purpose of reliability estimates is to eliminate those indictors that are ill-suited to the measurement of an underlying principal factor latent construct (Nunnally, 1975, p. 10). In order to achieve reliable results, multi-item scales ought to be purified. To this effect, the psychometric constructs should be operationalised through a battery of manifest measures that all reflect their underlying theoretical trait perfectly to the greatest possible extent in a *content sampling* sense. Yet, under the premise that indicators are randomly drawn from a common conceptual domain and that the construct score is defined as a composite measure of its indicator variable scores, the computation of a composite value is only meaningful if the focal latent factor is acceptably unidimensional (Gerbing & Anderson, 1988, p. 186 f.). This assumption is met if the measurement variables are both highly inter-correlated and attributable to their underlying construct. From this it follows that residuals should be uncorrelated because otherwise there may be a third variable effect that accounts for the shared non-random error variance in measurement items through a parallel pattern of relationship (Gefen, 2003, p. 26).

Given that factorial **unidimensionality** is prerequisite for reliability, psychometric tests should generally commence with the assessment of scale dimensionality (Gerbing & Anderson, 1988, p. 190). Traditional first-generation criteria (e.g. Cronbach's alpha and Dillon-Goldstein's ρ, which are delineated in the following paragraphs) are not sufficient for testing the dimensionality of a given factor structure, since they solely test for internal consistency of items. In so doing, these statistics apriorically assume external consistency in terms of the patterning of indicator cross-correlations (Segars, 1997, p. 116). Therefore, it is generally recommended by psychometricians to undertake **exploratory factor analysis** (EFA) as a preliminary technique for scale construction (Urbach & Ahlemann, 2010, p. 18). Accordingly, this study employs EFA to judge the appropriateness of the specified outer models and to optimise the measurement instruments by item selection where applicable.

EFA's primary purpose is to identify the underlying factor structure among a set of scale items with as few factors (structural dimensions) as possible by establishing the factor loading patterns of manifest measures (Hair, et al., 2010, p. 93). It is thus an interdependence technique that allows to investigate and to reduce where necessary the dimensionality of a given measurement instrument. For reflectively measured constructs it is assumed that items are one-dimensional with respect to a single extracted factor (Gerbing & Anderson, 1988, p. 191). In applied settings in which the sample size exceeds 250 cases, scale dimensionality can be assessed by means of principal component analysis using the *Kaiser criterion*, which is based on the **eigenvalue** measure (Meister, 2012, p. 196; Tenenhaus, 2005, p. 16). The eigenvectors of a rotated correlation matrix of factor loadings indicate the number of extracted factors. Because an eigenvalue of 1 represents a substantial amount of variation, the eigenvalue of the first principal component should be greater than 1 and the second smaller than 1 to meet the Kaiser criterion (Field, 2009, p. 640).

After verifying the factor structure's unidimensionality, further quantitative evaluation of the outer models' reliability is required. The **reliability of an indicator** quantifies the size of a standardised indicators' outer loading

λ (Bagozzi & Yi, 2012, p. 14). The square of an indicator's outer loading is also referred to as *communality of an item* and indicates how much of the variation in an item is explained by the underlying construct. At a minimum, the reliability coefficient shall be greater than 0.7 to assure that at least 50% of the indicator's variation are due to the construct of interest (Hulland, 1999, p. 198; Nunnally, 1975, p. 10). In exploratory studies where item batteries are newly developed, literature suggests also a threshold of 0.4 – indicators with lower loadings are to be discarded from the measurement model (ibid.).

In order to estimate the **statistical significance** of the outer loadings obtained in a distribution-free PLS-SEM context, inferential resampling procedures such as bootstrapping and jackknifing can provide standard errors for significance tests (Chin, 1998a, p. 318 ff.; Chin, 2010, p. 659). Either resampling procedure randomly draws subsamples from an original population sample to obtain empirical confidence statements that may compensate for biases in statistical estimates. Consequently, nonparametric resampling techniques supersede the theoretical distribution function of parametric normal-theory approaches by an empirical distribution that approximates the true population distribution of a specific path coefficient. In accordance with jackknifing, for all subsamples a predefined number of cases (*d*) is omitted, so that each subsample should span the original data set with the first *d* cases being deleted. Contrarily, the bootstrapping procedure holds that each subsample is obtained through random sampling with replacement from the original data set, but without omission of cases. As a rule, the number of bootstrap samples must be at least equal to the number of observations in the original sample (Henseler, et al., 2009 p. 305). Based on the mean value and standard deviation of the generated bootstrap distribution, robust confidence intervals can be calculated by means of pseudo t-tests (Hair, et al., 2016 p. 153). Using the estimated standard errors computed across all bootstrapping samples, the null hypothesis can be tested that the factor loading is de facto not significantly different from zero. As a consensus among social scientists, estimated coefficients should meet a significance level of 5% which corresponds to a critical t-value of 1.66 for a one-tailed test (Bartlett, et al., 2001, p. 45). Since jackknife performs less well (Efron & Gong, 1983, p. 39), this research study will adopt the bootstrap method.

When using multi-item measures, the extent to which constructs demonstrate reliability becomes a major concern (Churchill, 1979, p. 70). For assessing the reliability of a measurement model at composite level, PLS-SEM typically draws on both *Cronbach's alpha* and *Dillon-Goldstein's rho* as estimates of a latent variable's **internal consistency** (Henseler, et al., 2009 p. 298 f.). The traditional Cronbach's alpha criterion quantifies the degree to which items of a scale covary on average when the latent variable increases, providing an estimate of the common-factor-concentration (Cronbach, 1951, p. 321). Alpha-values above 0.6 are regarded acceptable in empirical research settings (Hair, et al., 2016 p. 112). A major deficiency of the coefficient alpha is its implicit assumption of summated scales which holds that all indicators of a battery have equal weights. By way of contrast, PLS prioritises manifest variables in correspondence with their individual loadings on the relevant construct (Henseler, et al., 2009 p. 299). Technically, the alpha coefficient is therefore less compatible with the working principles of PLS-SEM. In addition, the precision of Cronbach's alpha is sensitive to the number of scale items and features a general tendency to underestimate the internal consistency of latent constructs in PLS path models (ibid.). On these grounds, the present study chooses to use additionally the Dillon-Goldstein's rho (more commonly known as *composite reliability*) for ascertaining internal consistency of measurement scales.

As opposed to Cronbach's alpha, **composite reliability** ρ_c does not assume 'tau equivalency' among scale items and provides less conservative reliability estimates (Chin, 1998a, p. 320). More formal, the ρ_c index expresses the ratio between the individual component loadings (rather than the alpha's equal weightings) and the total variances of the respective indicators. Thus, composite reliability indicates the capability of a latent variable to explain the variance of its block of indicators. According to Bagozzi and Yi (2012, p. 17), the minimum level of composite reliability should be .70. Levels inferior to this threshold indicate a lack of reliability and require corresponding scale adjustments. Yet, it should be noted that very high levels of internal consistency close to a value of 1.0 may imply semantically redundant items, which are also not desirable in terms of their adverse consequences on content validity (Hair, et al., 2016 p. 112; Tavakol, et al., 2011 p. 54). Furthermore, prior research implies that the composite reliability measure tends to slightly overestimate intra-scale reliability. Therefore, in current literature it is advocated to consider both the more conservative Cronbach's alpha and the composite reliability measure ρ_c to assess the degree of item homogeneity (Hair, et al., 2016 p. 112).

The last methodological step in evaluating reflective measurement instruments is the assessment of validity, which is commonly subdivided into **convergent validity** and **discriminant validity** (Henseler, et al., 2009 p. 299). Convergent validity is proven when measurement variables correlate positively with alternative indicators of the same underlying trait (Hair, et al., 2016 p. 112; Bagozzi, et al., 2012 p. 18). It thus indicates how well indicators of a block measure what they are intended to measure. Fornell and Larcker (1981) propose using the **average variance extracted** (AVE) criterion for estimating the magnitude of measurement error. The AVE measures "the amount of variance that is captured by the construct in relation to the amount of variance due to measurement error" (Fornell & Larcker, 1981, p. 46). Assuming that all indicators are standardised, AVE would reflect the average of the communalities in a given block (Chin, 1998a, p. 321). An AVE of more than 0.5 is considered to be sufficient in literature, meaning that less than 50% of the variance that is captured by the construct is due to measurement error.

Discriminant validity describes the extent to which a theoretical construct empirically discriminates from other constructs within a given conceptual framework (Hulland, 1999, p. 199). This means that measurement variables should not share too much variance with measures of other conceptual variables in a nomological network. Consequently, the first approach in assessing discriminant validity is typically an examination of **cross-loadings**, whereby the indicator's factor loadings on their theoretically associated construct shall be greater than all of their cross-loadings on conceptually distinct constructs (Hair, et al., 2016 p. 115). However, since this criterion is considered to be rather liberal (especially in cases, where two neighbouring constructs are perfectly correlated), in PLS communities it is frequently advised to employ the *Fornell-Larcker criterion* to check for discriminant validity (Hair, et al., 2011 p. 146; Hair, et al., 2016 p. 118). Statistically, discriminant validity is indicated if a construct's AVE is greater than the common variances of this construct with any other of the model's constructs (Götz, et al., 2010, p. 696; Fornell & Larcker, 1981, p. 46).

From a conceptual standpoint, though, the efficacy of Fornell-Larcker's criterion is subject to PLS-SEM bias effects (see chapter 6.1.2.2), why this approach fails to reliably detect discriminant validity problems (Henseler, et al., 2015 p. 116 ff.; Hair, et al., 2016 p. 118). Henseler et al. argue in (2015, p. 115 ff.) that the new **heterotrait-monotrait ratio** (HTMT) is technically superior to AVE in terms of the reliability of results. In a nutshell, HTMT

puts the ratio of the mean of between-trait correlations (i.e. bivariate correlations of indicators across model constructs) in relation to the geometric mean of the average within-trait correlations (i.e. pairwise correlations of indicators within a block). This measure thus performs more efficient in detecting discriminant validity. Even though there are no universally accepted standards yet, based on prior research the authors suggest a threshold value of 0.90; values exceeding this threshold indicate a lack of discriminant validity (ibid., p. 129 f.). In order to decrease HTMT, in a first step those indicators may be eliminated that deflate the construct's average within-trait correlations due to low correlations with other items in the same block. Likewise, researchers may also decrease between-trait correlations by dropping indicators that are strongly correlated with indicators in the opposing block or by reassigning these indicators to the opposing trait. Given that theory-based conceptualisation considerations support this, the second approach would aim at merging the problematic constructs in the specified nomological net. Ultimately, if discriminant validity still cannot be established, the path model has to be discarded (ibid). Table 6.1 below summarises the relevant criteria for reflective measurement model assessment.

Evaluation Criterion	Requirement
Item Reliability	
Factor Loadings	> 0.7
Internal Consistency Reliability	
Composite Reliability	≥ 0.7
Cronbach's Alpha	≥ 0.6
Convergent Validity	
Eigenvalue	$EV_1 > 1$; $EV_2 < 1$
Average Variance Extracted (AVE)	> 0.5
Discriminant Validity	
Fornell-Larcker criterion	AVE > squared correlations of construct with other constructs
HTMT	HTMT confidence interval does not include 1.0
Statistical Significance	
t-value	> 1.66 (one-tailed test; ~ error of 5%)

Table 6.1: Reflective measurement model evaluation criteria

6.2.5 Assessment of Formative Measurement Models

Contrary to reflective measurement instruments, formative measurement models concentrate on the causative drivers of a dependent marketing variable. By taking the form of different weighted facets of a theoretical construct, formative indicators allow to analyse the relative impact of actionable success factors on critical marketing parameters (Albers, 2010, p. 422). Because formative measures do not necessarily covary, the internal

consistency perspective of classical test theory cannot be directly transferred to formative contexts (Diamantopoulos, et al., 2008 p. 1216; Henseler, et al., 2009 p. 300; Bollen, et al., 1991 p. 312). Consequently, correlations among indicators of an index may not be sensibly interpreted, why traditional validity measures render irrelevant for quality assessment of formative instruments. Moreover, due to the implicit assumption of error-free measures in formative modes of measurement, reliability tests become inherently obsolete (Rossiter, 2002, p. 388). Thus, either concept of construct validity (i.e., convergent and discriminant validity) and reliability lose their meaning in the course of evaluating formatively operationalised constructs. Instead, due to causality reversal, theoretical rational and expert opinions play generally a more pivotal role for index evaluation (Hair, et al., 2011, p. 146; Götz, et al., 2010, p. 697).

As a result, under formative scenarios quality assessment is strongly focussed on testing validity at indicator level, basically reflected by **indicator relevance** approaches and **multicollinearity** checks. Specifically, the estimated weights of indicators provide information about the relative contribution of each facet to its construct (Chin, 1998a, p. 307). Notably, since PLS-SEM strives to maximize the explained variance of latent index variables in a multiple regression sense, outer weights are frequently smaller than reflective item's factor loadings (Götz, et al., 2010, p. 698). Given that formative indicators do not measure the same conceptual content, omitting an indicator from a coherent block would, however, carry the risk of altering the very nature of the construct itself (Diamantopoulos, et al., 2001 p. 272). The exclusion of indicators with even minor explanatory contribution could potentially undermine the content validity of their associated construct und ultimately lower the model's theoretical and empirical usefulness for researchers and practitioners alike (Coltman, et al., 2008, p. 1250; Diamantopoulos & Siguaw, 2006, p. 276). Some authors in the field argue that a purely data-driven a posteriori deletion of indicators would finally represent a trial-and-error philosophy which contradicts the domain-forming nature of indices (Heinecke, 2010, p. 87).

Thus, in lieu of the strength of the indicator-construct relationships, their significance becomes more important from a statistical conclusion validity perspective. The **significance of weights** should be assessed ex post upon the basis of *t-statistics* (Henseler, et al., 2009 p. 302). Analogous to significance tests in reflective contexts, the bootstrapping procedure lends itself to the computation of the accuracy of parameter estimates (Hair, et al., 2016 p. 153; Hair, et al., 2011 p. 146). Similarly, the critical t-values are to be at a significance level of 5%, which corresponds to a value of 1.98 for two-tailed tests. Again, it has to be emphasised that any attempt to purify composite indicators which entirely cover their construct's domain might bear negative consequences on content validity, provided that the elimination decision is divorced from any qualified theoretical or conceptual consideration (Hair, et al., 2016 p. 148; Bollen, 2011 p. 362).

Furthermore, a central demand on the construct validity of a multi-faceted construct is the pairwise linear independency among its formative indicators. From a methodological and interpretational view point, substantial collinearity among items would result in severe biases in parameter estimates, which make it difficult to ascertain the unique influence of individual indicators on their associated latent variable (Diamantopoulos, et al., 2001 p. 272; Götz, et al., 2010 p. 88). Because formative logic grounds on the principles of multiple regression, the outer weights would be systematically underestimated if the predictor variables would effectively explain a large portion of variance among each other (Cenfetelli & Bassellier, 2009, p. 693). Besides suppressed coefficient estimates,

high collinearity may also be reflected in reversed weight signs and inflated standard errors, resulting in reduced validity coefficients of intra-construct relations (Hair, et al., 2016 p. 142; Bollen, 2011 p. 365). Thus, theoretically independent indicators that, however, empirically prove to be an almost perfect linear combination of other block items, are likely to carry redundant information (Diamantopoulos, et al., 2001 p. 272; Gefen, et al., 2000 p. 69).

Literature suggests therefore to eliminate formative indicators with a high inter-item correlation, provided that content validity is not affected (Diamantopoulos & Siguaw, 2006, p. 267). To assess the level of **multicollinearity** among predictors of a formative index, the **variance inflation factor** (VIF) shall be tested (MacKenzie, et al., 2011, p. 317). This criterion portrays the reciprocal of the *tolerance statistic*, which expresses the proportion of variance of one manifest variable that is not explained by the other predictors in the same block ($1-R^2$). To this end, all indicators of an index have to be regressed iteratively on the other items of an index. According to Hair et al. (2017, p.143), a VIF value of 5.0 or greater indicates a problematic collinearity level, whilst a minimum level of 1.0 represents perfectly orthogonal relationships between the block indicators. Table 6.2 shows the relevant evaluation criteria for formative measurement models.

Evaluation Criterion	Requirement
Indicator Relevance	
Outer Weights	No minimum level; interpretation of the magnitude of contribution of each formative indicator
Statistical Significance	
t-value	> 1.98 (two-tailed test; ~ error of 5%)
Multicollinearity	
Variance Inflation Factor	< 5.0

Table 6.2: Formative measurement model evaluation criteria

Once the outer models have been evaluated and found to possess satisfactory test results in regard to their reliability and validity, the empirical assessment should proceed at structural level. The subsequent chapter therefore expands on test criteria that allow to judge the magnitude, direction and significance of causal inter-construct relationships.

6.2.6 Assessment of the Structural Model

As opposed to covariance-fitting approaches which intrinsically rely on conventional parameter-based techniques, in distribution-free PLS-SEM contexts the structural model is assessed on the basis of heuristic criteria. These statistics can generally be determined by the inner model's predictive capabilities. In an OLS sense, predictiveness includes the path model's predictive power, predictive relevance and the magnitude of the structural effects (Chin, 1998a, p. 316). First off, the **path coefficients** serve as an initial orientation point in the assessment of the overall model's nomological validity. They represent the causal relationships linking the hypothesised latent variables,

whereby their standardised values usually range from -1 to +1 (Hair, et al., 2016 p. 195). Structural model path coefficients close to +1 signify strong positive correlations et vice versa for negative relationships.

In regard to the magnitude of regression coefficients, Information Systems-related literature typically suggests that standardised values should be at least .20 and -.20 respectively in order to be regarded as meaningful (Chin, 1998b, p. xiii). On the contrary, some researchers in the PLS community also tolerate beta coefficients of .10 in explorative stages of research (e.g. Ravens, 2014, p. 161; Arnhold, 2010, p. 230; Lohmöller, 1989). Considering the newness and complexity of the hypothesised structural model, the present study accepts relationships with path coefficients greater than or equal to .10. The causal links may still contain valuable insights and should only be discarded from the model if they prove to be statistically non-significant. Similar to the reliability of outer weights in measurement models, the significance of an estimated path coefficient is contingent upon its standard error that can be obtained from bootstrapping as preferred resampling method. Conventionally, critical **t-values** for two-sided tests should be significant at the 5% alpha level, what corresponds to a minimum value of 1.98 (Heinecke, 2010, p. 92). On condition that the structural path is satisfactorily significant and the path sign is consistent with the apriorically postulated direction of effect, the standardised beta coefficient provides a partial empirical validation of the respective hypothesis (Henseler, et al., 2009 p. 304).

Furthermore, the predictive power of a path model can be quantified by means of the **coefficient of determination** R^2-criterion (Chin, 1998a, p. 316). The R-squared measure determines the proportion of variance of an endogenous construct that is explained by its preceding latent variables in the structural model. It is calculated by relating the predicted to the actual values of a latent construct (i.e. the portion of explained variance to total variance). Therefore, the R^2-criterion can take values between zero and one, measuring the regression function's 'goodness of fit' against empirical data (Götz, et al., 2010, p. 701). According to Chin (1998a, p. 323), an R-squared value of 0.67 can be interpreted as being substantial, whilst values of 0.33 and 0.19 respectively indicate moderate and weak levels of explanatory power. However, it has to be noted that no universal statement can be made in regard to generalisable cut-off points for a sufficient predictive accuracy. This is because the determination coefficient intrinsically depends on the number of exogenous model constructs, whereas partial models that seek to be parsimonious – as opposed to full models – are intended to explain only a few relevant aspects of a phenomenon and thus do not strive for R^2-values near one (Schulze, 2009, p. 99; Götz, et al., 2010). Therefore, in highly complex research disciplines comprising multicausal phenomenona such as consumer behaviour even values of .20 are perceived as high (Hair, et al., 2016 p. 199). Accordingly, following Falk and Miller (1992, p. 80) this study strives for multiple determination coefficients ≥ 0.1.

The structural model evaluation should proceed with the analysis of **effect sizes** at structural level (Chin, 1998a, p. 316). Following traditional partial F-tests, Cohen derives in (1988) the f^2-measure which is defined as the increase in R^2 relative to the proportion of unexplained variance of the dependent latent variable. The effect size f^2 thus provides information about the substantive impact of a specified exogenous construct on its endogenous variable (Chin, 1998a, p. 316). The change in predictive power is calculated by estimating the path model twice, once with the exogenous latent variable included, and once more with the exogenous variable excluded (Hair, et al., 2016 p. 201; Götz, et al., 2010 p. 702). Values for effect sizes f^2 of 0.02, 0.15, or 0.35 respectively suggest the

latent predictor variable's weak, moderate or substantial influence on the focal endogenous variable (Cohen, 1988, p. 413; Götz, et al., 2010, p. 702).

Another important assessment criterion for evaluating the basic inner model involves the assessment of collinearity among exogenous constructs (Hair, et al., 2016 p. 192). To this end, the same measures can be applied as those that are relevant for formatively operationalised measurement models (cf. chapter 6.2.5). Here, the VIF metric can be utilised to identify the extent of linear dependencies among the preceding latent variables of an endogenous construct. Likewise, the tolerance value should not fall below .20 (what corresponds to a VIF value above 5). In cases of critical collinearity, Hair et al. (2016, p. 194) recommend eliminating respective constructs, merging of predictors, or conceptualising higher-order latent variables.

Finally, literature suggests to test the **predictive relevance** of reflective endogenous constructs by means of the *Stone–Geisser's* Q^2. The implementation of the test criterion Q^2 "[…] follows a blind-folding procedure that omits a part of the data for a particular block of indicators during parameter estimations and then attempts to estimate the omitted part using the estimated parameters. This procedure is repeated until every data point has been omitted and estimated" (Chin, 1998a, p. 317). The number of blindfolding rounds always equals the omission distance *D*, which implies which data point of the focal construct's indicators has to be eliminated. Formally, the Q^2-measure reflects the ratio between the sum of squares of the model prediction errors (i.e. the differences between the true values and the predicted values) and the sum of squares of trivial prediction errors (i.e. the differences between the mean values of the remaining data of the blindfolding procedure and the observed values). The Stone-Geisser's test criterion thus represents a measure of how well the empirical data can be reconstructed on the basis of the structural model (Götz, et al., 2010, p. 702). The correlational analysis framework is considered to have predictive relevance, if $Q^2 > 0$, whereas results of $Q^2 < 0$ imply a lack of predictive validity (Chin, 1998a, p. 318).

Evaluation Criterion	Requirement
Structural Effects	
Path Coefficients	> 0.1 or < -0.1
Statistical Significance	
t-value	> 1.98 (two-tailed test; ~ error of 5%)
Predictive Power	
R^2	> 0.1
F^2	≥ 0.15
Predictive Relevance	
Stone–Geisser's Q^2	> 0
Multicollinearity	
Variance Inflation Factor	< 5.0

Table 6.3: Structural model evaluation criteria

Table 6.3 outlines the relevant criteria for evaluating the quality of the inner model. If heterogeneity is assumed to be present in the structural model, the respective contextual circumstances are to be investigated (Chin, et al., 2003, p. 192). Accordingly, the following subchapter is devoted to the analysis of salient moderating variables.

6.2.6.1 Analysis of Moderating Effects

In many practical applications including the fields of Information Systems and consumer behaviour, the assumption that the empirical data stem from a single population that is homogenous in perceptions and evaluations is quite counterfactual (Sarstedt, et al., 2011, p. 196). Therefore, by integrating the two moderating variables 'innovativeness' and 'personal experience', the conceptualised Wearable TAM attempts to account *ex ante* for striking disparities in parameters in respect of different subpopulations in technology markets. Here, a moderating variable is defined as "[...] a variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable" (Baron & Kenny, 1986, p. 1174). Thus, apriorically identified moderating relationships potentially enhance the predictive validity of endogenous variables. In accordance with Baron and Kenny (ibid.), these contextual variables can be of either qualitative (such as gender or social class) or quantitative nature (e.g. consumer psychological constructs like arousal). In literature the importance of grouping variables is repeatedly emphasised in so far that moderators may significantly contribute to the understanding of complex causal structures, as implied for instance by contingency theory (Henseler & Fassott, 2010, p. 715; Chin, et al., 2003, p. 193). Generally, moderation effects can be inspected by means of **multigroup analysis** to test for differences between identical models for distinct groups or, alternatively, under consideration of **interaction effects** that influence specific model relationships (Hair, et al., 2016 p. 243 f.).

When employing a multigroup analysis, the study population is segmented by the focal categorical moderator variable into group-specific subpopulations (Eberl, 2010, p. 496). The parameters of the same PLS path model are then separately estimated in each of the different subsamples. Subsequently, the moderation effect can be determined on the basis of group comparisons. However, multigroup analysis is suboptimal for both unobservable constructs that ought to be measured via multi-item scales and continuous variables. The latter limitation is especially because conducting multiple pairwise group comparisons quickly boosts the familywise error rate, i.e. conducting multiple tests at a certain significance level is associated with an increase in the overall probability of a Type I error (Mooi & Sarstedt, 2011, p. 136). On the other hand, dichotomisation of variables inevitably entails a certain degree of information loss and arbitrariness in the assignment of observations to groups (Henseler & Fassott, 2010, p. 721). Given that the two behaviourally relevant moderators identified so far both represent abstract unobservable traits, it is clearly advisable to employ multiple metrically-scaled indicators for operationalisation of the underlying latent interaction constructs (Hair, et al., 2016 p. 246). This study should thus apply an interaction-term approach.

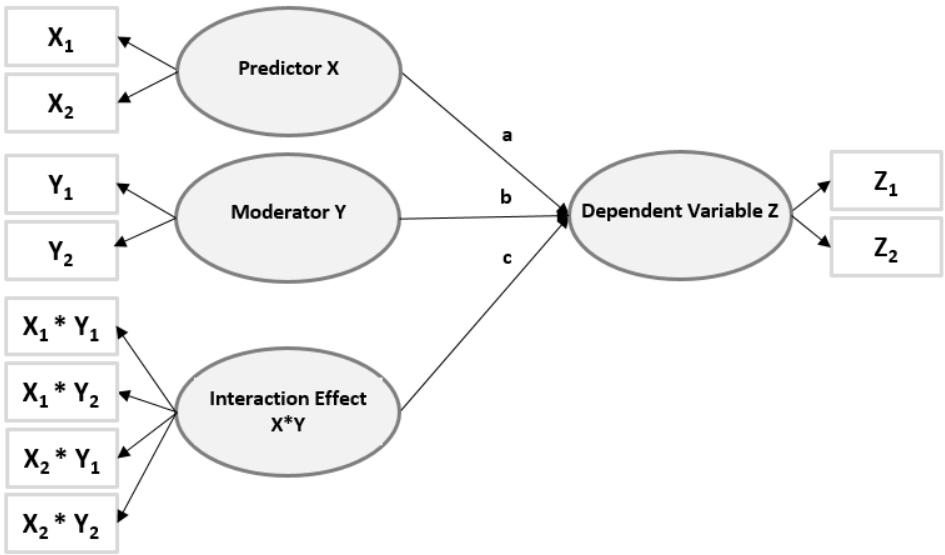

Figure 6.3: General PLS moderator model (Based on Chin, et al., 2003, p. 198)

To accurately estimate contingent relationships in PLS path models, Chin, Marcolin and Newsted (2003, p. 190 ff.) propose using a *product-indicator approach*, in which the standardised indicators of the latent predictor and moderator variables are cross-multiplied to form interaction terms. Along with the direct influence of the segmentation variable, the Cartesian product of the predictor and the moderator flows into the evaluation of the model-inherent interdependencies. Figure 6.3 illustrates the concept of a PLS moderator model with three reflectively operationalised variables and X being the predictor, Y the moderator, and Z the dependent variable. The interaction term is added to the main effects model as an additional latent variable X*Y, whereby the pertinent regression parameter c indicates the strength of the contingent effect of the moderator Y on the relationship between the exogenous variable X and the endogenous variable Z. Mathematically, this path model can be expressed as follows:

$$Z = a * X + b * Y + c * (X * Y) \tag{6.6}$$

where X * Y represents the interaction term that is added to the structural model. Hence, the slope of the exogenous construct X dependents upon the level of the latent segmentation variable Y. In order to properly assess the interaction effect, there are basically four approaches available (Henseler & Chin, 2010, p. 84): the product term approach, the orthogonalizing approach, a hybrid and a two-stage approach (for a more detailed introduction to these approaches, see Henseler & Chin, 2010). Considering its relatively high level of statistical power in cases of many indicators and observations, its ease of use, and its applicability to formative measurement models, this study gives preference to the two-stage approach for creating interaction terms (Hair, et al., 2016 p. 253; Henseler, et al., 2010 p. 724). Essentially, this method runs the main effect PLS path model in the first stage in order to obtain latent variable scores (Henseler & Fassott, 2010, p. 724). In the second stage, the interaction term is modelled as the element-wise product of the standardised factor score estimates. To determine path coefficients, the interaction term is then utilised as an independent variable in a multiple linear regression on the endogenous variable score.

With regard to the measurement model assessment, a latent moderator variable must meet all criteria of reliability and validity as outlined in chapter 6.2.4. Given the correlative nature of the interaction term variable, however, common psychometric property standards become meaningless by design (Hair, et al., 2016 p. 255). In order to evaluate moderating effects at structural level, the direct relation of the interaction term and the endogenous latent variable shall be examined (Henseler & Fassott, 2010, p. 730). The moderation hypothesis is supported, if the regression coefficient *c* emerges as statistically significant (Baron & Kenny, 1986, p. 1174). Again, for determining that a particular interaction effect actually exists (i.e. as a function of the moderator variable in the target population to which the researcher intents to generalise the results), Henseler and Fassott (2010, p. 730) recommend applying the non-parametric **bootstrapping** procedure under a PLS-SEM point of view.

The substantive impact of the moderator variable on a specific causal path can be analysed with the aid of the f^2 **effect size** (Chin, et al., 2003 p. 195; Hair, et al., 2016 p. 256). In a moderation context, the effect size is calculated by contrasting the R^2 of the main effects variables with the R^2 of the full moderator model consisting of the same main effects model plus the interaction terms. However, conventionally defined guidelines for small, medium and large effects do not hold for moderation analysis. Aguinis et al. (2005, p. 102) have found in their meta-analysis that the median observed effect for moderation is only .002 both in experiments and in field studies. Accordingly, Kenny (2015) proposes using 0.005, 0.01, and 0.025 for small, medium, and large interaction effects, respectively, as a more realistic standard. Yet, the author emphasises that even these values may be 'optimistic' in light of the review findings of Aguinis et al.

6.2.6.2 Analysis of Mediating Effects

Since behavioural models in consumer research and related disciplines become increasingly complex, recent structural models are typically subject to mediation effects (Hair, et al., 2013, p. 4). In order to gain insights into how effects hinder or support each other in complex nomological networks, especially in explorative stages of research practitioners are highly advised to test and report routinely mediation effects (Nitzl, 2016, p. 25). Eventually, the analysis of indirect effects may provide a more complete picture of the interplay of the intervening latent variables. Hence, to underpin the Wearable TAM's theoretical assumptions of partially mediated cognitive beliefs (H_{3a} and H_{4a}) with empirical results, the incorporated mediation hypotheses should be explicitly examined.

Mediation occurs if a third variable intervenes between an exogenous construct and the dependent variable such that there are two causal paths directed towards the target construct in a three-variable system (Baron & Kenny, 1986, p. 1176). The basic mediation model is diagrammed in Figure 6.4. Therein, the nature of the hypothesised direct effect *c* is governed by the mediator variable, which intervenes as a systematic influence between the independent latent variable and the dependent latent variable via the indirect effect a*b. As opposed to moderator variables, mediator variables itself represent predictor variables that are intrinsically explained within the nomological network, why their impact is directly implemented in PLS path models. Consistent with the typology established by Zhao et al. (2010, p. 200), three patterns can be identified in a simple mediation model: (a) complementary or **partial mediation**, where the indirect and the direct effect both prove to be significant and have the same direction of action, (b) **competitive mediation**, where the indirect and the direct effect both prove to be significant but have an opposite direction of action due to a *suppressor effect* (i.e. one of both competing paths absorbs the effect of the other), and (c) indirect-only or **full mediation**, where solely the indirect effect exists, but

not the direct one. Determining the type of mediation requires analysing the respective partial structures of the three-variable system separately.

Again, testing for the quality of statistical mediation models necessitates all involved latent variables to meet both the psychometric properties and the quality criteria for structural path models as proposed in the previous subchapters (Hair, et al., 2016 p. 235). Notably, prior research analyses of the significance of mediational models were dominated by the *Sobel z-test* (Sobel, 1982, p. 290 ff.) as recommended by Baron and Kenny in (1986, p. 1177). The Sobel test compares the strength of the indirect effect a*b with the squared standard errors of the structural parameters *a* and *b*. However, this formula assumes multivariate normality for the standard error of the distribution of the indirect effect a*b. In addition, Preacher and Hayes found that the z-test statistic is low in power compared to bootstrap techniques (2004, p. 722). Therefore, Zhao et al. (2010, p. 204) advise strongly against the use of the normal-theory approach by Sobel. Instead, researchers should perform bootstrap tests for determining mediation effects.

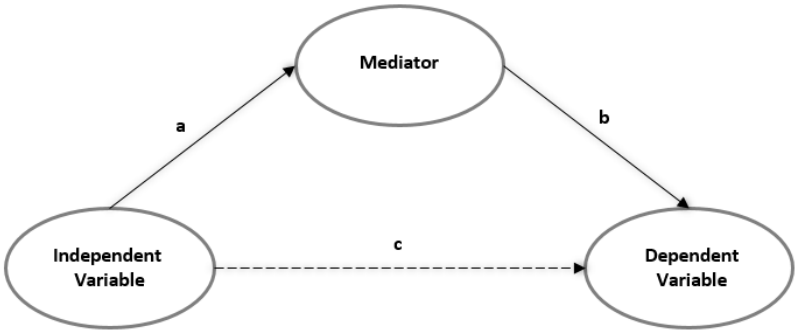

Figure 6.4: General PLS mediation model (Based on Baron & Kenny, 1986, p. 1176)

Complementary to the analysis of the significance of mediating effects, the relative magnitude of the indirect effect can be quantified by means of the **variance accounted for** (VAF) measure (Eberl, 2010, p. 500). The VAF criterion depicts the ratio of the indirect effect (a*b) over the total effect (a*b+c) on the outcome variable. This quotient expresses what proportion of the total effect of the predictor is due to the indirect effect. In case of a full mediation the VAF measure takes on the value of 1.00, since the outcome variable's variance is then fully explained by the mediation process. Conversely, VAF estimates can become negative or even exceed the value of 1.00 if suppression occurs (Shrout & Bolger, 2002, p. 434). Given that the indirect pathways are significant, as a rule of thumb a VAF value between 0.20 and 0.80 indicates a typical partial mediation, whereas a mediation proportion greater than 80% characterises a full mediation (Nitzl, 2016, p. 20). Nonetheless, even though the VAF criterion may provide deeper insights into mediation models, this measure should be interpreted with caution, particularly in situations where suppression is present (i.e. in cases of competitive mediation or negative mediation proportions, c.f. ibid).

6.2.6.3 Analysis of Higher-Order Structures

In addition to unidimensional measurement models, latent variables can also be conceptualized in terms of higher-order hierarchical constructs, which involve more than one dimension (Wetzels, et al., 2009, p. 178; Jarvis, et al., 2003, p. 204; Chin, 1998b). Higher-order latent variables are therefore not directly connected to manifest measures.

In principle, the dimensionality of a construct depends on the level of abstraction of its conceptual definition. Although the abstraction level might be raised infinitely, due to the increasing complexity, however, in practice the application of hierarchical constructs is usually limited to second-order factors (Šarić, 2012, p. 159). The benefit of higher-order constructs grounds primarily on the theoretical and structural parsimony they provide to the nomological network they are embedded in (Wetzels, et al., 2009, p. 178). Also, in situations characterised by critical collinearity among formative indicators, establishing second-order structures can solve discriminant validity problems (Hair, et al., 2016 p. 281).

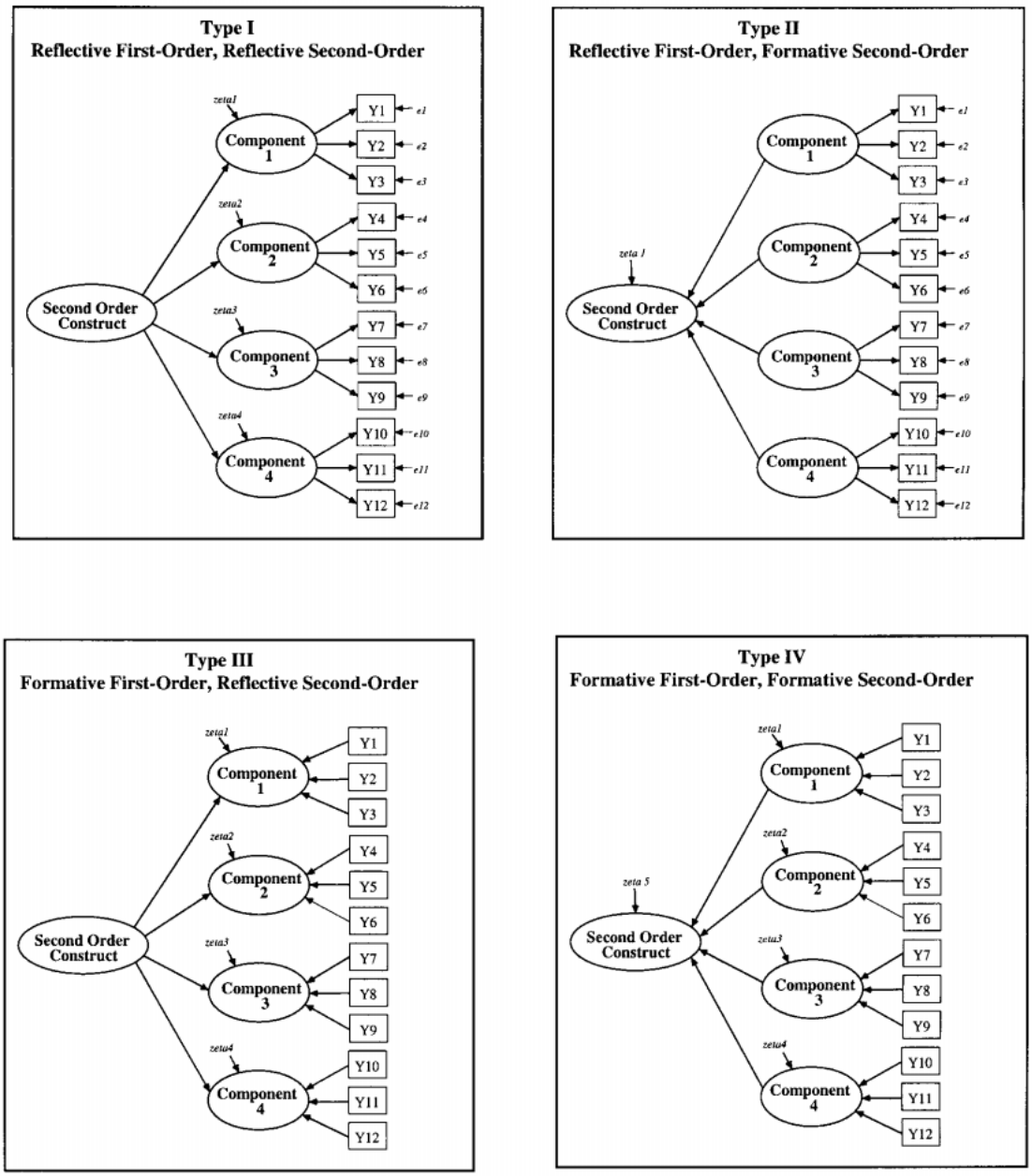

Figure 6.5: Possible operationalisation approaches in second-order factor models (Jarvis, et al., 2003 p. 205)

As is apparent from the two possible measurement philosophies for each of both levels of a second-order model, there are four alternative conceptualisation approaches for hierarchical models as illustrated in Figure 6.5:

- Type I (reflective-reflective): This hierarchical model contains only reflective measures at both first- and second-order level. However, since the second-order construct might just as well be measured directly by means of the second-order indicators, some researchers question the purpose of such models (Šarić, 2012, p. 160).
- Type II (reflective-formative): This model consists of reflective indicators for the first-order latent variables and formative first-order constructs that are, themselves, indicators for the underlying second-order construct. Since the error term is measured at the level of the manifest measures associated with the first-order constructs, this model is considered the most suitable type.
- Type III (formative-reflective): From a conceptual perspective, this model is particularly problematic, as the first-order latent variables, which are measured formatively, represent themselves reflective and, thus, interchangeable indicators.
- Type IV (formative-formative): Here, both the first-order and the second-order constructs are conceptualised according to the formative mode, what may be particularly fruitful for success driver studies.

In the present study, the latent variables *Perceived Pervasiveness* and *Perceived IT Security Risk* are defined as Type II second-order constructs (see chapter 6.3 on the operationalisation of the reflective, lower-order measurement models).

In technical terms, there are three approaches to model hierarchical latent variables in PLS-SEM: (1) the repeated indicator approach, (2) the two-stage approach, and (3) the hybrid approach (Wilson & Henseler, 2007, p. 791 ff.; Becker, et al., 2012, p. 365 ff.). The **repeated indicator approach**, originally suggested by Wold in (1982), uses the indicators of all first-order constructs as direct measurement variables at higher level to operationalise a second-order latent variable. This remedy allows estimating the higher-order and lower-order dimensions simultaneously by means of standard PLS algorithms. Results from a Monte Carlo simulation study show that this modelling approach should be used for Type II hierarchical component models, as it produces more precise parameter estimates and more reliable higher-order factor scores (Becker, et al., 2012, p. 376). However, when modeling formative hierarchical component models (Type II and Type IV), almost all of the higher-order constructs' variance is explained by the lower-order layer. This may prove problematic from an overarching nomological network perspective, since any further structural path that points to the focal multidimensional construct will render insignificant due to the model's artificially correlated residuals (Ringle, et al., 2012, p. 8). In addition, according to the research community, the repeated indicator approach is only advisable if the first-order constructs are measured by the same number of indicators (Becker, et al., 2012, p. 366), a condition which is nevertheless met in this study.

Contrarily, for the **two-stage approach**, the factor scores of the latent first-order constructs are computed in a first stage analysis without incorporating the second-order dimension. Subsequently, these first-stage construct scores are used as manifest variables for the higher-order latent construct in a second-stage model. Similar to the repeated

indicator approach, the **hybrid approach** repeats the manifest variables of the fist-order constructs at second-order level. However, this technique splits all indicators randomly so that half of the measures are represented on the first-order latent predictor and the other half are represented on the second-order construct side (Wilson & Henseler, 2007, p. 792). Hereby, each indicator is used only once in a model. This may overcome the criticism towards the interpretational confounding introduced by the two-stage approach. On the downside, however, the hybrid approach diminishes the reliability of the measurement models having only half the number of manifest variables. In the context of PLS-SEM, which is known to be 'consistent at large', this appears particularly problematic.

Given that the study-inherent higher-order factor model *Perceived IT Security Risk* represents an endogenous construct and that its first-order latent variables have an equal number of indicators, this study uses a mixture of the repeated indicator approach and the two-stage approach as recommended in (Ringle, et al., 2012, p. 8): In the first stage, the repeated indicator approach is utilised to obtain the latent factor scores for the lower-order constructs, which then, in the second stage analysis, can serve as indicators for the higher-order construct. Principally, reflective-formative second-order constructs are subject to the same assessment criteria as first-order formative constructs (see chapter 6.2.5), i.e. they have to be evaluated by means of indicator weights, significance of weights, and multicollinearity of indicators (Becker, et al., 2012, p. 376 f.). Finally, it should be noted that Type II models require the use of the inner path-weighting scheme to ensure more precise parameter estimates and a more reliable second-order factor score (ibid.).

6.3 Operationalisation of Constructs

According to the two-language-theory by Carnap (1966), theoretical concepts have to be translated into corresponding terms at empirical level in order to become quantifiable. Operationalisation thus relies on the assumption that latent constructs can be inferred from their observable effects. Therefore, applying the logic of 'content sampling', appropriate indicators or descriptive items have to be identified, which are based on the conceptual domain of the construct in question and entirely cover its semantic scope (Hox, 1997, p. 60 f.). The following sections delineate the selection of appropriate measurement instruments for each of the study-inherent traits and behavioural attributes.

Following the recommendations and common practice in psychometrics (Churchill, 1979 p. 66; Hair, et al., 2016 p. 45), the operationalisation of the Wearable TAM variables relied thoroughly on approved measurement models in personality psychology, marketing, and Information Systems research. These scales are characterized by a high reliability and validity as evidenced by prior research. Since this study focusses on the emerging phenomenon of wearable computing acceptance, some adaptions, however, had to be made to calibrate the theoretical concepts to the given study context. Furthermore, given that multiple-item scales are often psychometrically superior to single-item scales and that all of the main constructs in this study refer to conceptually more abstract, subjective phenomena which are perceived as heterogonous by raters, exclusively multi-item scales were employed (cf. Rossiter, 2011, p. 1566 ff.). As opposed to 'global' single-item questions, multi-item measures facilitate tests of the internal consistency of latent variables and increase scale precision by enabling the discrimination of finer

degrees of an attribute (Churchill, 1979, p. 66). Churchill sets forth that by using multi-item scales, the specificity of individual items having a common conceptual core can be averaged out when they are combined. To converge upon the true population values, SEM literature advocates the use of three items per construct (Iacobucci, 2009, p. 95; Bergkvist & Rossiter, 2007, p. 177).

In order to obtain viable metrics in a PLS environment, all measurement instructions for the indicators (except the moderating variable 'past experience') were oriented towards the rating scale instrument developed in chapter 7.1.3, i.e. the question items were deployed on seven-point Likert-scales, anchored at the extremums 1 = "strongly disagree", and 7 = "strongly agree". Basically, for the sake of content validity all item pools were derived from literature and translated into German as the native language of the respondents. To assure consistency in the wording of items, the questions were compared to a retranslated version. The following paragraphs address in a first instance the operationalisation of reflective measurement models and then proceed to the specification of higher-order and formatively measured latent variables.

6.3.1.1 Reflective Measurement Models

The measurement instruments presented in this chapter are operationalised pursuant to a reflective measurement philosophy. This means, the causality flows from the latent variables to their measures, and all indicators are expected to be interchangeable and intercorrelated, having the same antecedents and consequences.

As theoretically derived in chapter 3.1.2.1, the behavioural intention to use wearables represents a conative component of attitude in the sense of a proximate nomological predictor of the actual acceptance behaviour. Literature suggests a unifactorial structure of conation, why this study operationalises the *intention* variable accordingly on the basis of three manifest measures as proposed in (Putrevu & Lord, 1994, p. 83). Since the original measurement model is tailored towards advertised products, the question items were transferred to the context of wearable computing adoption. In addition to the anticipated probability of a future usage of wearables ('AZ03_01') and related intentions ('AZ03_03'), the tendency for a trial usage ('AZ03_02') is also queried by the set of items. The applied item battery is presented in Table 6.4.

Indicator	**Item**	**Source**
BEHAVIOURAL INTENTION TO ADOPT WEARABLES		
AZ03_01	It is very likely that I will use wearables	Putrevu & Lord, 1994, p. 83
AZ03_02	I will definitely try out wearables	Putrevu & Lord, 1994, p. 83
AZ03_03	As soon as it's possible I will use wearables	Putrevu & Lord, 1994, p. 83

Table 6.4: Scale on behavioural intention to adopt wearables

Due to its ability to explain differences in information processing and decision-making styles, involvement is another key construct having a long tradition in consumer behaviour research (Rothschild & Houston, 1980, p.

655). As a result, to date there is a plethora of divergent taxonomies and operationalisation approaches in the literature. For instance, Zaichkowsky (1985, p. 341 ff.) argues in favour of the semantic differential scale, which allows to judge the emotional and cognitive relevance of a given study object on a rating scale composed of 20 bipolar pairs of adjectives. On the contrary, Laurent and Kapferer (1985, p. 43) understand this individual difference variable as a multi-faceted construct stemming from different types of antecedents. The authors contend, that the various categorisations of consumer involvement (e.g. 'enduring' and 'situational' involvement, which reflect the stability of personal concern with a product class) would highlight the great importance of the *sources* of involvement. Its facets are thus to be analysed in the first place. Nevertheless, in view of the specificity of the present structural model and the analytic research objective of explaining the inter-individual variance in acceptance behaviour, this construct is considered a unidimensional, general commitment expression of the consumer towards wearable computing. The operationalisation of involvement is adapted from the *Personal Involvement Inventory* (PII) by Zaichkowsky (1994a, p. 350), which is originally composed of 10 scale items. Common factor-analytic evidence, however, has led the researcher to conclude that there is one general factor accounting for the most variance in the items and one minor component. As a result, the inventory has been grouped into two subscales representing a cognitive and an affective aspect (Zaichkowsky, 1994b, p. 62). Against the backdrop that it is mainly the affective aspect of involvement that carries behavioural relevance in an adoption decision context (Bosnjak, et al., 2007, p. 603), the behavioural intention to use wearables focusses on the respective item group of the PII. It should be noticed, that the original semantic differential scale is transferred into a *unipolar* Likert scale for the present study purposes, e.g. item 'IV01_01' measures the intensity of fascination towards wearable computers. Otherwise, the indicator coding for involvement would be inconsistent with the specification of the other measurement scales of this study. Furthermore, the item 'IV01_02' is reverse coded for data cleansing reasons (cf. chapter 7.1.4) as can be seen in Table 6.5.

Indicator	**Item**	**Source**
INVOLVEMENT TOWARDS WEARABLES		
IV01_01	Wearables are fascinating	Zaichkowsky, 1985, p. 350
IV01_02 (REVERSED)	Wearables are boring	Zaichkowsky, 1985, p. 350
IV01_03	Wearables are exciting	Zaichkowsky, 1985, p. 350
IV01_04	Wearables are appealing	Zaichkowsky, 1985, p. 350

Table 6.5: Scale on the involvement towards wearables

The three-item scale *trust in technology* addresses the reasonable expectation or confidence of an individual that a certain, newly emerged technology provides the anticipated functionality and performs helpful and predictable to the greatest extent possible. In line with the empirical studies of Armida (2008) and Jarvenpaa et al. (1999), this tripartite construct was conceptualised as being unidimensional and thus reflectively measured by means of a single scale. The items proposed by Armida in (2008, p. 42) were adapted with regard to the context of the trustworthiness of wearable computing. In using this scale, the researcher refers to the original scale on store

trustworthiness developed and validated by Jarvenpaa et al. (1999). Table 6.6 displays the employed measurement items for the perceived trust in wearable technologies.

Indicator	Item	Source
TRUST IN WEARABLES		
NZ05_01	Wearables will be trustworthy	Armida, 2008, p. 42
NZ05_02	I will not need to be cautious with wearables	Armida, 2008, p. 42
NZ05_03	I think wearables will work well	Armida, 2008, p. 42

Table 6.6: Scale on trust in wearables

At compound trait level of the personality-related correlates, the Wearable TAM hypothesise that there are basically two reflectively measured latent variables, which potentially explain commitment behaviour in innovative IT markets, namely 'Need for Materialism' and 'Need for Cognition'. The former personality variable captures the importance a consumer attaches to worldly possessions as manifested in high levels of material consumption (Belk, 1984, p. 291). This thesis' view fits well with the concept of instrumental materialism, which considers acquisition to be a means to desired end goals such as longevity and happiness, rather than an end in itself (Founier & Richins, 1991, p. 405). Similarly, Shrum et al. (2013, p. 1185) understand materialistic behaviours as a vehicle for self-identity and hedonic goals and, thus, as being also intrinsically motived. Under this definition, materialism emphasises self-signalling over social-signalling. Complementarily, recent research has found that affective processes in terms of positive, product-evoked emotions are actually implicated in materialism (Richins, 2013, p. 14 ff.). To investigate this personality trait, this study uses the materialism scale developed by Richins and Dawson (1992, p. 304 ff.). They constructed an 18-item scale consisting of the three underlying, moderately correlated factors 'success', 'centrality', and 'happiness'. In line with the focal working definition, which assumes that materialism represents an orientation towards acquisition as the pursuit of happiness, this study focusses on the 'happiness' component (see Table 6.7). From multiple validation tests, for the five-item happiness subscale the researchers report a coefficient alpha ranged between .73 and .83.

Indicator	Item	Source
MATERIALISM		
PS02_04 (REVERSED)	I have all the things I really need to enjoy life	Richins and Dawson, 1992, p. 310
PS02_05	My life would be better if I owned certain things	Richins and Dawson, 1992, p. 310
PS02_06 (REVERSED)	I wouldn't be any happier if I owned nicer things	Richins and Dawson, 1992, p. 310

Indicator	Item	Source
PS02_07	I'd be happier if I could afford to buy more	Richins and Dawson, 1992, p. 310
PS02_08	It sometimes bothers me that I can't afford to buy all the things I'd like	Richins and Dawson, 1992, p. 310

Table 6.7: Scale on materialism

In contrast to materialism, the second trait 'Need for Cognition' (NFC) describes the intrinsic enjoyment individuals derive from engaging in effortful cognitive endeavours (Petty, et al., 1986, p. 1033; Fortier & Burkell, 2014, p. 2). This motivational factor varies along a bipolar continuum form a high to low dispositional tendency to expend cognitive effort. Individuals high in need for cognition naturally tend to seek information, prefer complexity and enjoy cognitive stimulation, whereas individuals low in need for cognition are more likely to rely on cognitive heuristics or cues as primary basis for their judgements (Cacioppo, et al., 1996, p. 198). This relatively stable (albeit not invariant) personality trait was operationalised using four items from the original NFC-scale propagated by Cacioppo et al. (1982, p. 121). As demonstrated in earlier research studies, this measurement instrument is characterized by high reliability and validity (Sadowski, 1993, p. 453). However, during the pre-test half of the respondents stated that one item ("I primarily think because I have to", reversed item no. 25 from the original NFC-scale) would be less comprehensible and meaningful. This item was therefore excluded from the final questionnaire (see Table 6.8).

Indicator	Item	Source
NEED FOR COGNITION		
PS03_01 (REVERSED)	Simply knowing the answer rather than understanding the reasons for the answer to a problem is fine with me	Cacioppo et al., 1982, p. 121
PS03_02	I prefer my life to be filled with puzzles that I solve	Cacioppo et al., 1982, p. 121
PS03_04	I would prefer complex to simple problems	Cacioppo et al., 1982, p. 121

Table 6.8: Scale on need for cognition

Against the backdrop that personality characteristics do relate to socio-economic factors such as occupational attainment, in social sciences and Information Systems research there is a growing interest to extend the scope of research models without psychological focus to the realm of personality psychology (Hahn, et al., 2012, p. 355; Devaraj, et al., 2008, p. 93). Likewise, this study attempts to integrate latent individual traits into the technology acceptance model in order to explore their influence on IT adoption behaviour. According to the influential and

most extensively researched 'Big Five' framework for the description of personality structure (see John & Srivastava, 1999, p. 102 ff.), the elemental trait level of the present structural model consists of five latent variables. These five psychological constructs were measured using a 10-item extra-short scale version of the well-established **Big Five Inventory** (BFI), the BFI-10 (see Rammstedt & John, 2007, p. 203 ff., and Rammstedt, 2007, p. 193 ff.). In responding to the need in multi-topic and panel survey settings for an abbreviated version of the traditional, lengthy personality instruments (with the most comprehensive scale, the *NEO Personality Inventory* by Costa and McCrae, 1992, comprising 240 questionnaire items and taking about 45 minutes to complete), Rammstedt and John devised in (2007, p. 203 ff.) a short multidimensional scale based on the well-proven BFI-44 instrument developed by Benet-Martinez and John (1998, p. 729 ff.). The economic BFI-10 scale shows respectable psychometric properties in terms of retest reliability, structural validity, and convergent validity in both German and English samples (Rammstedt & John, 2007, p. 209 f.). The instrument consists of one true-scored and one reverse-scored item per scale, both covering core aspects of each Big Five dimension. This thesis followed this measurement approach and adopted all ten scale items (see Table 6.9).

Indicator	**Item** *I see myself as someone who…*	**Source**
NEUROTICISM		
PS01_04 (REVERSED)	…is relaxed, handles stress well	Rammstedt & John, 2007, p. 210
PS01_09	…gets nervous easily	Rammstedt & John, 2007, p. 210
EXTRAVERSION		
PS01_01 (REVERSED)	…is reserved	Rammstedt & John, 2007, p. 210
PS01_06	…is outgoing, sociable	Rammstedt & John, 2007, p. 210
AGREEABLENESS		
PS01_02	…is generally trusting	Rammstedt & John, 2007, p. 210
PS01_07 (REVERSED)	…tends to find fault with others	Rammstedt & John, 2007, p. 210
OPENNESS		
PS01_05 (REVERSED)	…has few artistic interests	Rammstedt & John, 2007, p. 210
PS01_10	…has an active imagination	Rammstedt & John, 2007, p. 210
CONSCIENTIOUSNESS		
PS01_03 (REVERSED)	…tends to be lazy	Rammstedt & John, 2007, p. 210
PS01_08	…does a thorough job	Rammstedt & John, 2007, p. 210

Table 6.9: Scale on personality

Moreover, since this study likely targets a heterogenous sample (see chapter 5.3), two relevant moderating variables – 'Personal Innovativeness' and 'Prior Experience' – were incorporated into the Wearable TAM to add to the explanative power of the final model. The factor *personal innovativeness* focusses on the individual willingness to try out new products and behavioural patterns in the specific domain of information technology. Consequently, individuals who score high in personal innovativeness are deemed to possess an innate propensity to be more innovative with computers and, thus, to be more predisposed to adopt new technologies (Agarwal & Karahanna, 2000, p. 677). This background variable was measured by utilising the rating scale constructed by Agarwal and Prasad (1998, p. 210) (see Table 6.10). The authors report an alpha of 0.84, what can be regarded as a highly satisfactory level of internal consistency (cf. chapter 6.1.2.4).

Indicator	**Item**	**Source**
INNOVATIVENESS		
ZS05_01	If I heard about a new information technology, I would look for ways to experiment with it	Agarwal and Karahanna, 2000, p. 677
ZS05_02	Among my peers, I am usually the first to try out new information technologies	Agarwal and Karahanna, 2000, p. 677
ZS05_03	I like to experiment with new information technologies	Agarwal and Karahanna, 2000, p. 677

Table 6.10: Scale on innovativeness

The other study-inherent moderator 'prior experience' refers to the general familiarity with a computer system in terms of the level of general product expertise. Commonly, people who have more experience with an innovative technology are assumed to have already accepted the technology to a certain extent and, hence, to be situated further on the Rogers (1983) innovation adoption process model (see chapter 3.1.1). This is why the *prior experience* variable is considered a background factor rather than a direct predictor of adoption behaviour (Planing, 2014 p. 130). Unlike the other scale instruments developed so far, this variable is measured by means of a five-point Likert scale, capturing information about the familiarity with the term wearable computing:

- I am already very familiar with wearables
- I know what wearables are
- I've already heard the term 'wearables' once before
- I've never heard the term 'wearables' before

In regard to the higher-order structures of the Wearable TAM, at first-order level all latent variables – themselves jointly constituting the second-order layer of abstraction – give rise to observable measures. The causality flows thus from the lower-level latent variables to their indicators, which represent imperfect, interchangeable manifestations of their associated construct. Generally, to avoid psychometrically inferior single-item scales, every

lower-order latent variable was operationalised by means of at least three reflective indicators. In the following section, the operationalisation of the hierarchical component models is approached.

6.3.1.2 Higher-order Constructs

As indicated by the exploratory study findings in chapter 4.3, one striking feature which primarily generates the added benefit in a ubiquitous computing context is the *perceived pervasiveness* of a technology. According to the pioneering work of Karaiskos (2009, p. 174), the conceptual scope of the abstract pervasiveness construct is made up of three reflectively measured independent dimensions, namely **ubiquity**, **unobtrusiveness** and **context awareness**. Even though the author inductively derives and acknowledges the compound, multidimensional nature of the pervasiveness construct, his study does not investigate the joint effect of the partial aspects at structural model level. This view does not allow for exploring the individual impact of each pervasiveness facet on its mediating, global second-order construct. Also, the unique explanatory capacity of the overall perceived pervasiveness remains logically concealed. To address this theoretical and conceptual issue, the three pervasiveness subdimensions are conceived as formative indicators in the present study. The *Ubiquity* scale reflects the system's mobility and availability, whereas the *Unobtrusiveness* measurement items tap into the level of felt distraction or cognitive load caused by the technology. Complementarily, the *Context Awareness* inventory addresses the system's adaptability, proactivity, and the information relevancy it provides. Karaiskos' multidimensional scale of pervasiveness produced alpha values above .840 for all facets (2009, p.143). However, the original indicator batteries involve more than 7 question items per construct. Therefore, in order to decrease respondent fatigue and to avoid aborts, the sub-scales were reduced to three and five items. The items were adapted to measure the dimensions of pervasiveness with respect to wearable computers. Table 6.11 shows the employed measurement scale.

Indicator	**Item**	**Source**
UBIQUITY		
PV03_01	The wearable is available to use wherever I need it	Karaiskos, 2009, p. 151
PV03_02	The wearable is available to use whenever I need it	Karaiskos, 2009, p. 151
PV03_03	I am able to use the wearable anytime	Karaiskos, 2009, p. 151
PV03_04	The wearable is accessible everywhere	Karaiskos, 2009, p. 151
PV03_05	The wearable is always available to me	Karaiskos, 2009, p. 151

Indicator	Item	Source
UNOBTRUSIVENESS		
PV02_01	My attention does not need to be focused on the wearable the whole time	Karaiskos, 2009, p. 151
PV02_02	I don't have to concentrate fully on the wearable when using it	Karaiskos, 2009, p. 151
PV02_03	The usage of the wearable does not disrupt me from other activities	Karaiskos, 2009, p. 151
PV02_04	The wearable does not distract me too often	Karaiskos, 2009, p. 152
PV02_05	The wearable does not require continuous attention	Karaiskos, 2009, p. 152
CONTEXT AWARENESS		
PV01_01	Wearables are able to adapt to changing conditions (e.g. show track and heart rate during sports)	Karaiskos, 2009, p. 152
PV01_02	Wearables automatically adapt to the situation at hand	Karaiskos, 2009, p. 152
PV01_03	Wearables can automatically trigger actions relevant to the situation (e.g. in the case of smartwatches displaying the time when turning the wrist)	Karaiskos, 2009, p. 152

Table 6.11: Scale on pervasiveness

The second model-relevant construct having a more complex factor structure refers to the subjectively perceived *IT security risk*. In line with the classical conceptualisation in IT security literature, this construct was specified in terms of a formative second-order latent variable, which is composed of the sub-dimensions **confidentiality**, **integrity**, and **availability**. The latter two facets were operationalised by using the respective three-item-scales from Hartono et al. (2014, p. 19). The items, which originally assess electronic commerce transactions, were adapted to the special characteristics of wearable computing. Because the former scale on confidentiality developed by Hartono and colleagues (ibid.) does not fit the need of this study, the instrument was replaced by a more appropriate measurement scale taken from Dillon and Lending (2010, p. 29). Their empirical acceptance study investigates the privacy of patient-care Information Systems in hospitals and can be easily transferred to the

given study object. The researchers reported an alpha of .81 for their original privacy measure, which consists of five items. Two of these items, however, focus strongly on the peculiarities of patient-care systems. Therefore, only the remaining three items were adapted for the present study (see Table 6.12).

Indicator	Item	Source
AVAILABILITY		
NZ02_04	I could not use the wearable due to hardware failure (e.g. defective sensors)	Hartono et al., 2014, p. 19
NZ02_05	I could not use the wearable due to network failure	Hartono et al., 2014, p. 19
NZ02_06	I could not use the wearable due to software failure (e.g. crashing apps)	Hartono et al., 2014, p. 19
INTEGRITY		
NZ06_01	My data could be processed or transmitted incorrectly by the wearable	Hartono et al., 2014, p. 19
NZ06_02	The recorded data could be altered	Hartono et al., 2014, p. 19
NZ06_03	The recorded information could be incorrect	Hartono et al., 2014, p. 19
CONFIDENTIALITY		
NZ07_01	I would feel my recorded data would not be secure from unauthorised use	Dillon and Lending, 2010, p. 29
NZ07_02	My recorded data could be used fraudulently by third parties	Dillon and Lending, 2010, p. 29
NZ07_03	Others could easily read confidential data recorded by my wearable	Dillon and Lending, 2010, p. 29

Table 6.12: Scale on perceived IT security

6.3.1.3 Formative Measurement Model

The utility characteristics of wearable computers are aggregated into a formative index describing the perceived potential of wearables for enhancing one's life. The formative specification of the usefulness measure may provide

valuable information on the relative importance of each block indicator in a success factor sense. This is very important, because knowing which indicator has what weighting on the construct makes it possible to derive actionable recommendations on where system design efforts should be targeted to. In stark contrast to the reflective mode, in a formative measurement model, the causality flows from the block of indicators to its associated latent variable. Consequently, the elimination of only one single non-redundant item would necessarily alter the entire conceptual domain of the focal construct.

According to the conceptualisation of perceived usefulness outlined in chapter 5.1.1.1, the utility facets are specified as being manifest measures, which are deemed to causally evoke the consumers' overall perception of pervasiveness benefits provided by wearable technologies. To measure the constructs' facets, the five items postulated by the quantitative research study on the impact of wearables in (Brauer & Barth, 2013, p. 3) were used. Because the original study questioned people who already used wearables, the wording was transferred into subjunctives, emphasising the fact that most German respondents do not possess a wearable computer yet (see Table 6.13).

Indicator	**Item** *I think, wearables could…*	**Source**
PERCEIVED USEFULNESS		
NZ04_01	…boost my personal abilities.	Brauer and Barth, 2013, p. 3
NZ04_02	…improve my health and fitness.	Brauer and Barth, 2013, p. 3
NZ04_03	…boost my self-confidence.	Brauer and Barth, 2013, p. 3
NZ04_04	…help me feeling more in control of my life.	Brauer and Barth, 2013, p. 3
NZ04_05	…enhance my social relationships.	Brauer and Barth, 2013, p. 3

Table 6.13: Scale on perceived usefulness

6.4 Chapter Conclusions

The objective of this chapter was to develop a data analysis approach that allows to increase credibility of the inductively derived research framework. Therefore, in taking a critical realist position this chapter discussed and justified an empirical falsification of the developed set of hypotheses. Based on the research questions of the present study, the appropriateness of a quantitative confirmatory approach for validating the conceptual model was established. Since this research is set out to provide generalisable insights that underpin the theoretical assertions, a purely qualitative investigation would inherently fall too short. By quantitatively testing the exploratory study findings, the Wearable TAM may attain empirical corroboration in a post-positivist sense. Given the nature of the study subject which implicates latent and interrelated processes on individual-level, the applicability of structural equation modeling as technically preferable multivariate method was pointed out. Also, the choice of PLS-SEM

was justified under consideration of the characteristics of the synthesised Wearable TAM and the research aims. Subsequently, the relevant assessment criteria for both inner and outer models were presented.

Finally, measurement scales were developed in order to operationalise the hypothetical model constructs that resulted from the qualitative interviews along with the conceptual study. All items were based on approved and validated measurement models in literature and adjusted to the study context. Thereby, this research does not further 'inflate' the available body of construct definitions in literature and ensures comparability to other research models. That way, the theoretical concepts under examination were transformed into measurable factors which enable a quantitative evaluation of the postulated research model.

7 Empirical Analysis

Having determined the philosophical stance as well as both the statistical data analysis method and the measurement instruments, the next step is to choose appropriate methodologies for answering the two last research questions. This is done in section 7.1. Then, in sections 7.2 and 7.3 the proposed research model is validated at both construct and structural level on the basis of the chosen statistical quality criteria. Finally, the yielded estimation results are interpreted in depth.

7.1 Research Strategy

The formulated nomological net of cause-effect chains has to be examined quantitatively in order to determine (i.e. corroborate or falsify) correlation in the hypothesised relationships between the selected cognitive and personality-related acceptance factors. Accordingly, in response to the analytic research objective raised in section 1.2 ("To what extent do the identified factors of the integrative framework affect the acceptance phenomenon?"), the next research stage aims at either confirming or rejecting the derived hypothetical generalisations by assessing the quality of the theoretical assumptions against an empirical evidence-base.

Based on this research objective and the inherent validity requirements pertaining to an empirical establishment of causal inferences, an experimental research design appears to be most appropriate (Hair, et al., 2003 p. 42; Summers, et al., 2005 p. 120). However, laboratory or field experiments such as test markets are less viable for the present research purposes from both an economical and methodological viewpoint. Particularly, the proposed latent predispositions, by their very nature, cannot be manipulated actively within any experimental setup. In addition, one can hardly hold the various extraneous variables constant, which generally coincide with a complex nomological net of hypothetical constructs (de Vaus, 2005, p. 19). Following the traditions of empirical social science and Information Systems research, the present explanatory study therefore implements a nonexperimental, field-based research design that deals with a cross-section of data of the target population (Fischer, 2010, p. 142; Radhakrishna & Doamekpor, 2008; Malhotra, et al., 2006, p. 1865).

In view of the newly synthesised behavioural model that focusses on the *latent*, intrapersonal intention formation in innovative technology markets, meaningful secondary data is yet lacking within the intended scope. Hence, in order to be able to conduct the envisaged confirmatory analysis (deductive research) adequately, the required raw data should be gathered in the course of a primary study. Since survey research is best suited for positivist studies that focus on individuals as units of analysis (Bhattacherjee, 2012, p. 73), achieving this purpose should thus involve a field survey of consumer attitudes and perceptions.

In social sciences this vital data collection instrument is one of the most frequently employed techniques to test theories or hypotheses (Malhotra & Birks, 2007, p. 265). Survey techniques are commonly based upon the use of structured questionnaires given to a random sample of a specified population (ibid.). They provide a relatively cost-efficient approach to the study of large samples of respondents what increases the researcher's ability to make generalized probabilistic inferences about predetermined segments of social systems (Hair, et al., 2003 p. 256). Broadly, quantitative surveys can be classified according to the mode of questionnaire administration, for instance

as personal face-to-face interviews, postal questionnaires, telephone interviews, or electronically, e.g. mail surveys (Bowling, 2005, p. 282). Given their relative efficiency, global reach and flexible design (Evans & Mathur, 2005, p. 197), web-based surveys seem to be particularly fruitful for the purpose of the intended data collection phase. In addition, online approaches to survey research are deemed to be advantageous in that they eliminate interviewer interaction biases (e.g. stereotyping, halo effect, etc.), certain response biases (e.g. common rater effects such as social desirability) and data entry errors by means of greater anonymity and technology-based controls (Hair, et al., 2003 p. 269; Podsakoff, et al., 2003 p. 888). However, especially the second source of systematic measurement errors, which are commonly subsumed under the term **common method variance** (CMV), may be a concern when self-report questionnaires are used (Chang, et al., 2010, p. 178).

These spurious variances or 'measurement artifacts' shared among perceptual measures are attributable to the use of common measurement methods rather than to the constructs the measures represent (Podsakoff, et al., 2003, p. 879). CMV is problematic because it produces a false internal consistency of results and thus generates inflated estimates of reliability by the operation of common source factors (Chang, et al., 2010, p. 178; Lindell & Whitney, 2001, p. 114). Potentially, this could lead to either Type I or Type II errors. That is, the null hypothesis (H_0) could be erroneously rejected, et vice versa, what clearly would jeopardise the validity of conclusions (Lindell & Whitney, 2001, p. 119). Podsakoff et al. (2003, p. 882) identify four sources of method bias: common rater effects, item characteristic effects, item context effects and measurement context effects. In order to reduce any potential artifactual inflation of observed correlations, Chang and colleagues (2010, p. 179 ff.) suggest a range of both ex-ante and ex-post remedies. Ex-ante approaches involve primarily the way the questionnaire is designed and administered. On the contrary, ex-post strategies refer to measures of statistical analyses to detect and possibly control for any artefactual covariation.

The authors argue that complex specifications of regression models that are unlikely to be part of the respondents' 'cognitive maps' would correct for CMV (ibid., p. 180). Considering the structural complexity of the herein conceptualised network of multiply interrelated pre-purchase variables (the Wearable TAM), this may be the case for the present study. In addition, Malhorta et al. found that method biases in the field of Information Systems research are not as serious as compared to those in other disciplines (2006, p. 1881). Nonetheless, to account for potential common method biases the present study followed the measures compiled by Krosnick and Presser (2010, p. 264 ff.), MacKenzie and Podsakoff (2012, p. 545 ff.) and Chang et al. (2010, p. 179 ff.). The implementation of the utilised procedural remedies is addressed in detail in the respective sections on sampling procedure (chapter 7.1.2), questionnaire design (chapter 7.1.3) and data preparation (chapter 7.1.4).

Beside possible method biases, the utility of electronic surveys may be limited due to their comparably poor level of sample representativeness as computer-assisted inquiries naturally approach a more technophilic population (Matsuo, et al., 2004, p. 3998). Recent research studies show that there is indeed a significant association between socio-economic factors (particularly with regard to age and educational level) and Internet usage rates (Silver, 2014, p. 1030). However, accumulating evidence indicates that this gap is steadily narrowing and that the demographic structure of users with Internet access is becoming more and more representative of the population at large (Perrin & Duggan, 2015). Moreover, it should be noticed that in socio-economic terms there actually exists

a parallel between the segment of Internet users and the universe of early adopters of wearable computers (Goldberg & Hall, 2016). There are thus strong methodical grounds for drawing an on-line sample.

The methodological and research strategical foundations of the intended empirical analysis being set, the following subchapters will discuss details of the data collection process including both the sampling design (chapter 7.1.1) and sampling procedure (chapter 7.1.2) as well as the questionnaire design (chapter 7.1.3).

7.1.1 Sample Design

The target population of this study is defined as the population of potential adopters of wearables in Germany. With a focus on this country, this research seeks to understand adoption behaviour in a technologically and economically developed society. Given that technology adoption is significantly affected by the global attitude towards computer-based technologies, this involves individuals with a certain level of technical affinity (Buabeng-Andoh, 2012, p. 136; Nickell & Pinto, 1986, p. 301). Considering this very large study population focussed within the scope of the present research project, it may not be feasible to gather data from the entire target group. Therefore, a subset of individuals should be selected which is representative of the total population. In literature, probability sampling is recommended for survey research projects involving a vast overall population (Saunders, et al., 2009, p. 213). For probability sampling each population element has an equal, nonzero chance of being included in the sample to be drawn. As any generalisation inferred from a sample is based on statistical probability, the likely error in generalising decreases with an increasing number of sampling units, i.e. larger samples can be more confidently generalised to the target population than smaller ones (ibid., p. 217).

However, due to research economic reasons an acceptable minimum sample size has to be determined considering (1) the accuracy of a sample that is assumed to be tolerable, (2) the level of confidence needed, and (3) the estimated variance within the sample (Bartlett, et al., 2001, p. 44; Ahn, et al., 2014, p. 2):

(1) The **accuracy** of a probability sample (also referred to as margin of sampling error or level of precision) describes the range in which the true or hypothesised value of the population is estimated to fall. For instance, given an accuracy level of 0.05, if 70% of eligible sample units have adopted a new technology, then one can conclude that between 65% and 75% of subjects in the target population have actually adopted the technology. As can be seen from the confidence interval approach formula below (6.6), sample size varies inversely with the squared error rate. The critical value for this parameter is arbitrary, however, most scholars in social sciences agree that a margin of error rate of 5 percent is appropriate from a practical standpoint (Bartlett, et al., 2001 p. 45; Burns, et al., 2003 p. 375).

(2) The **level of confidence** (which is associated with the 'z value') refers to the level of certainty that the characteristics of the gathered data will reflect the actual characteristics of the total population (Saunders, et al., 2009, p. 218). This concept is axiomatically based on the *central limit theorem* that states that the distribution of sample means derived from a simple random sample will approximate a Gaussian normal curve given that the sample size n is sufficiently large, i.e. when $n \geq 30$ (Hair, et al., 2003 p. 339 f.; Russell Bernard, 2006 p. 173). This holds true even if the original population parameter is not normally distributed (Saunders, et al.,

2009, p. 340). As the sample mean value of a repeatedly sampled parent population fluctuates around the true mean value μ and entails an approximately normal distribution, there is a high probability that the mean of any sample drawn would converge upon the actual population mean (Saunders, et al., 2009, p. 340; Friedman, 2015, p. 162). Transferred to the concept of confidence this implies that if a 90% level of confidence is selected, 90 out of 100 samples will have approximately the true population value within the specified range of accuracy. Statistical confidence is incorporated into the formula for sample size determination (see equation 6.6) by employing the *z* value for the defined level of confidence. Conventionally, in social sciences and information research literature a confidence level of 95% (corresponding to a *z*-statistic of 1.96) is considered to be adequate (Albers, 2017 p. 26).

(3) The **degree of variability** within a sample refers to the range of attributes in the population (Singh, et al., 2014 p. 10). As a consequence, sample size determination can be regarded as a function of the social heterogeneity: the more heterogeneous a population, the larger the required sample size to arrive at a fixed level of precision (ibid.). Since no preliminary data on the primary variables of interest exist for the purpose of the present study (e.g. from pilot study results) the population structure has to be estimated a priori (Bartlett, et al., 2001, p. 45). Consequently, sample size calculation becomes inherently hypothetical (Ahn, et al., 2014, p. 2). Considering that a proportion of 50% indicates the maximum social heterogeneity in terms of a 50 to 50 percent split in responses, most researchers recommend to assume a proportion of 0.5 in such instances, where the population structure is unknown (Krejcie & Daryle, 1970, p. 607 ff.; Israel, 1992, p. 2; Hair, et al., 2003, p. 345).

Based on these three components the required minimum sample size can be calculated according to Cochran's formula for large and non-finite populations (1977, p. 75):

$$n_0 = \frac{(z)^2 * (p)(1-p)}{e^2} = \frac{(1.96)^2 * (0.5)(1-0.5)}{0.05^2} = 384.16 \approx 385 \tag{6.6}$$

which is valid where n_0 is the sample size, z represents the abscissa of the normal sampling distribution curve that cuts off the defined α-score at the tails (which corresponds in this case to a confidence level of 95% for two-sided tests), p denotes the supposed standard deviation in the population (the current calculations are conservatively based on a proportion of 0.5), e is the acceptable tolerance level of error (in the present case 0.05).

Aside from an adequate statistical significance, another important goal in correlation studies is to avoid Type II or false-negative errors in hypothesis testing (i.e. to decrease the probability of incorrectly accepting the null hypothesis). Inversely related to the probability of a Type II error is the **statistical power** of a test, which is defined as a direct function of the sample size and the effect size (in terms of the magnitude of a treatment effect) (Konstantopoulos, 2009). In order to compute a sample size required to achieve a target for statistical power, researchers typically use power tables such as those published by Algina et al. (2003). As per convention, statistical power is set to .80, i.e. there is a 20% chance of erroneously accepting the null hypothesis when the alternative hypothesis is true (Prajapati, et al., 2010 p. 10). A commonly used measure for the overall effect size of a regression model is Cohen's f^2 (Aguirre-Urreta, et al., 2015 p. 36). Assuming a medium effect size of about .15 for the model

predictors (see chapter 6.2.6) and given 12 predictors in the research model, the required sample size for a two-tailed test and a target power of .80 is 357 (cf. the power table for multiple regression analysis by Algina, et al., 2003, p. 319). Still, this number is below the calculated sample size based on the desired level of confidence. As this study seeks for a nationally representative cross-sectional sample of individuals in Germany, a minimum of 385 observations is hence prerequisite. The next section outlines the chosen strategy to reach this minimum acceptable sample size. the lowest path coefficient

7.1.2 Sampling Procedure

In order to gather efficiently the primary data, participants were recruited via the online panel *Toluna Inc.* (Toluna USA, Inc., 2016a), i.e. the sample was bought from a panel provider who rewards participants in sponsored surveys. This service provider has been chosen due to its longstanding experience, panel size and membership at several industry associations that are concerned with developing guidelines for panel management and data quality (Toluna, Inc., 2018). Due to the widespread availability of the Internet among various groups, online research panels are increasingly utilised as a valid, cost-effective and efficient mean of data collection (Roster, et al., 2004, p. 359 ff.; Toft, et al., 2014). According to Couper, collecting cross-sectional datasets from pre-recruited panels of Internet users with regard to certain quota adheres to probability-based sampling approaches (2000, p. 487 f.). In support of this, a great number of researchers in the field of social inquiry argue that, due to the massively increased Internet penetration rate, the representativeness of collected data from Internet has become increasingly akin to data from probability-based general population samples (Salsman, et al., 2014, p. 4).

Yet, it has to be stated that pre-recruiting of panel members *per se* may not meet the criteria for probability sampling in a narrower sense, since pre-recruiting techniques inevitably involve some degree of self-selection at the point of inviting new panel members (Arnhold, 2010, p. 198; Loosveldt & Sonck, 2008, p. 94). Nonetheless, several empirical studies have found that results from web panels differ only modestly from the outcomes of traditional modes of survey (Hansen & Pedersen, 2012, p. 238). Moreover, with regard to the total market, Olsen points out that online panel surveys would finally introduce a *different*, rather than an *additional* self-selection process compared to e.g. mail sampling (2009, p. 607). In the course of a consumer preference study on the valuation of non-market goods, the author shows that the selection bias differences between Internet panel and mail surveys are of minor importance (ibid.). Considering the fairly broad nature of the present sampling frame, reflecting actual and potential adopters of wearable computing, and trading off accuracy requirements and analysis expectations against cost and operational concerns, a web panel recruitment strategy appears to be a suitable data collection approach (Arnhold, 2010, p. 202).

The consolidated Toluna online access pool comprises about 352.000 community members in Germany (Toluna.com, 2016, p. 23), who voluntarily registered on the web site and expressed their willingness to participate in incentivized online surveys. The panel provider concerned guarantees high data quality by means of diverse standard operating procedures (Toluna USA, Inc., 2016b). For example, GeoIP (a form of geolocation based on IP addresses) as well as postal code validations are used to verify that the panelists provide valid postal addresses. Further procedures for data quality control are described on the provider's website (Toluna USA, Inc., 2016b).

According to MacKenzie and Podsakoff (2012, p. 546), aligning the difficulty of surveys with the capabilities of respondents (i.e. selecting participants who have the required experience thinking about the issue of interest) would reduce artifactual covariation among perceptual measures. Thus, in order to ensure that the sample is representative of the population-of-interest as regards a minimum level of technical affinity, a cross quota with slight restrictions on income and educational structure was selected by the panel provider. That is, to ascertain response accuracy, the sample was drawn from a recruitment cohort that closely reflects the relevant socio-demographic characteristics – otherwise, there would be a chance that participants with lacking technical understanding might generate a considerable amount of non-plausible data. It has to be noticed in this context that several survey methodologists explicitly suggest to employ certain quotas in order to adjust the sample composition to the target population (Terhanian & Bremer, 2012, p. 755; Craig et al., 2013).

Following approval by the 'Science and Environment' faculty research ethics committee at Plymouth University, adult subjects were recruited from the German population by the Internet survey company (Toluna USA, Inc., 2016a). All prospective participants were verified extensively and underwent checks to ensure their identity and location. In addition, to prevent duplicate enrolments, double opt-in procedures together with the application of cookie-based technologies during the panelist-registration process were employed as an integral part of the panel provider's ongoing quality-control measures (Toluna USA, Inc., 2016b). After having screened the panel members for eligibility, potential study participants were sent electronic invitations from Toluna and asked to complete the on-line questionnaire as outlined in chapter 7.1.3. For survey completion, each sample unit obtained incentive-based compensation from Toluna in terms of panel points worth 2,05 €, which could be redeemed for cash or for vouchers for selected shops and services.

The first wave of the fieldwork was conducted from July 13, 2016 – July 15, 2016. During this period 425 study participants started the questionnaire, of whom 385 completely filled-in the questionnaire (i.e. the target number of individuals to ensure estimation accuracy as agreed with the panel provider). This corresponds to a satisfactory cumulative completion rate of 90.6 %, what can be considered as a reasonably high ratio with regard to an opt-in online panel setup (DiSogra & Callegaro, 2015, p. 2; Louviere, et al., 2013, p. 28). However, to further mitigate issues of over- and underrepresentation, additional participants were recruited via postings in diverse discussion boards. For the present research, several Internet forums were targeted, some of which focussed on technical topics (e.g. https://forum.garmin.de/) and others which were thematically open (e.g. https://forum.unicum.de/ and https://www.surveycircle.com).

These on-line tools for Internet-mediated interviewing are effective one-to-many communication channels through which new information can diffuse rapidly within a certain online community (Saunders, et al., 2009, p. 350). According to Ridings and Gefen (2004), virtual communities can be defined as social groups of peers with shared characteristics such as behaviours, beliefs or interests. This intra-group homophily leads to an enormous information potential, turning discussion boards into even more effective communication instruments as compared to classical direct marketing channels (Garg, et al., 2011, p. 11 ff.). Along with technically-oriented bulletin boards that were targeted, this study included also non-technical web forums in order to reduce sampling bias, i.e. to avoid an overrepresentation of technophiles. This second-wave survey was administered from July 19, 2016 – August 31, 2016. In total, 216 further respondents started the computer-mediated interview, of whom 144 answered the

survey completely, what results in a total of 529 cases. Likewise, the corresponding survey completion rate (66.7%) can be regarded as fairly satisfactory with respect to web-based surveys (Archer, 2008).

7.1.3 Questionnaire Development

Essentially, the survey design should serve to test the hypotheses of the Wearable TAM. The devised questionnaire therefore comprises a set of questions that operationalise and measure the theoretically relevant constructs proposed (see Appendix B.1). More precisely, those question items reflect manifest measures which quantify the underlying latent study constructs in terms of proxy variables at empirical level. In doing so, they bridge the gap between the theoretical construct and the phenomenal observation. Principally, scale construction was based on the procedure proposed by Churchill (1979, p. 64 ff.). This means, a precise understanding of the constructs was first developed in the course of the conceptualisation of the structural model (cf. chapter 5). Then, appropriate measurement items were adopted from literature and, where necessary, adjusted to the given study context. The applied measurement models for the latent Wearable TAM variables were introduced in detail in chapter 6.3. Thereafter, the questionnaire design has been developed as described in the following sections.

As stated before, data collection was done through field research by means of a web-based online survey. In respect of effectiveness, this asynchronous mode of communication allows for a dynamic questionnaire design including the rotation of items and real-time data consistency checks (Gediehn, 2010, p. 114). The online questionnaire was programmed with the web-based service *SoSci Suvey* (SoSci Survey GmbH, 2015), because it provides free available and completely customisable survey templates and data collection tools. With regard to the SEM requirements, the questionnaire was designed in a standardised format with *structured questions*. In terms of response completeness and data analysis facilitation, this question format is well suited for transforming qualitative phenomena into quantitative measures (Hair, et al., 2003 p. 424). Hence, to account for the confirmative nature of the study, all questions were asked in a closed-ended manner and single choice design.

The assignment of numbers to categories of responses (e.g. scale points) is commonly referred to as *coding*. Since coding determines the scale type that most likely satisfies the study objectives, this process is crucial for scale development (Hair, et al., 2016 p. 9). In general, scaling involves a continuum upon which measured attributes of objects are located according to a set of rules, such as allocating numerals corresponding to the empirical intensity of a behaviour (Bradley, 2007, p. 209). Overall, there are four basic types of measurement scales, each of which provides an ascending level of admissible mathematical operations on measurement results, namely **nominal scales** (quantities can only be classified), **ordinal scales** (quantities can be ordered), **interval** or cardinal scales (intervals between adjacent ranks are equal, so that the difference between ranks can be determined), and **ratio scales** (there is a meaningful zero, so comparison of absolute magnitudes is possible and the ratio of scale values can be computed) (Churchill, et al., 2010 p. 234; Easterby-Smith, et al., 2008 p. 230 f.).

In social science research, attitudinal scales are widely used to measure latent phenomena which are not numeric in nature, e.g. opinions, mental dispositions and preferences (Kumar, 2011, p. 157). Strictly speaking, the problem of attitude measurement suggests an ordinal interpretation of attitude scales. However, empirical data are frequently to be analysed with techniques designed for cardinal measurements to fulfil the requirement of *equidistance* (Hair, et al., 2016 p. 9). This means, the measurement scale must use equally spaced intervals as units

of measurement, each category having equal importance or 'attitudinal value', such that the self-reported attitude intensity of one person can be measured in relation to the gathered attitudinal score of another individual.

To enable multivariate data analysis with multiple PLS-regression models at interval level, **Likert scaling** was employed. Likert scales represent summative scales ranging from a group of ordered response categories – from least to most – for measuring unidimensional concepts of scientific interest in general and cognitive-based beliefs in particular (Hair, et al., 2003 p. 422; Likert, 1932 p. 5 ff.). Even though Likert scales serve to collect ordinal-level data, they behave more like interval scales provided that they possess clearly defined qualifiers for each category. Also, scale items shall be symmetrically distributed on each side of a neutral middle alternative, which allows to indicate either emotional ambivalence or indifference (Hair, et al., 2016 p. 9; Krosnick, et al., 2010 p. 274). In terms of scale granularity, there has been much debate among psychometricians concerning the optimal number of scale items (Finstad, 2010, p. 105; Krosnick & Presser, 2010, p. 268). On the one hand, more sensitive scales evidently permit to maximise information retrieval due to higher discriminating power. Conversely, less fine-grained scales tend to contribute to improper measures through subtle but repeated data loss (Finstad, 2010, p. 109). However, human mind has a limited short-term memory span capable of discriminating about 7±2 different stimuli at once, what implies a cognitive numeric limit of about seven items for making one-dimensional judgments (Preston & Colman, 2000, p. 2; see also the original article by Miller, 1956, p. 343 ff.). In line with this, several studies show that seven-point scales are preferable to maximize reliability and validity (Krosnick & Presser, 2010, p. 272). This study therefore employs a seven-point, unipolar Likert scale with both extremums “strongly disagree” and “strongly agree” as well as the midpoint category “neither agree nor disagree”.

In accordance with the native language of the survey participants, the catalogue of questions was originally prepared in German. To address and prevent potential common method biases, the final questionnaire was developed according to Krosnick’s and Presser’s recommendations in (2010, p. 264 ff.) and MacKenzie’s and Podsakoff’s *ex ante* strategies in (2012, p. 545 ff.) for controlling method bias in questionnaire design. The authors emphasise that when respondents are unwilling or unable to expend the necessary cognitive effort to answer accurately to a long series of questions, their responses become more prone to method bias (MacKenzie & Podsakoff, 2012, p. 545). Particularly in web-based, single source studies, where the researcher is not present when the questionnaire is completed by the respondents, the appearance of the questionnaire and especially the first impression is germane to the credibility and overall response rate of a survey (Planing, 2014 p. 145; Podsakoff, et al., 2003 p. 887).

As a consequence, the introductory remarks on the cover page of the questionnaire implement remedies for the respondent’s susceptibility to ‘satisfice’ (i.e. to apply cognitive decision heuristics to generate satisfactory answers) in that they assure the respondents of the anonymity and confidentiality of the study, that it is their personal opinion that is of importance, and that there are no right or wrong answers (MacKenzie & Podsakoff, 2012, p. 548 f.; Krosnick, 1991, p. 214). Additionally, to increase trust and to mitigate suspicions the introduction page briefly outlines the study purpose and provides information on the author, the affiliated institution, and the approximated duration for completing the questionnaire. Furthermore, an electronic informed consent has been integrated into the start page to conform to the relevant ethical requirements. Also included was a note of thanks to the respondents in advance for taking the time to fill out the questionnaire.

Even though there are no well-established procedures for an optimal question design, various versions of conventional guidelines and procedures are offered in pertinent methodology textbooks. Krosnick and Presser (2010, p. 264) agree that the most valuable design rules in this common wisdom include e.g. a clear and simple wording and syntax which allow an easy interpretation and do not push respondents towards an answer. Vague and complex concepts should always be clarified by clear examples and explanations to decrease the likelihood of satisficing (MacKenzie & Podsakoff, 2012, p. 546). With regard to the abstractness of the taxonomy of ubiquitous computing, this is of particular importance for the present study. Therefrom, to reduce response bias the second page of the online questionnaire contains a short definition of the term 'wearable computing' including the two most prominent examples of this novel IT class – 'smartwatches' and 'smart glasses' – so as to create a common conceptual understanding.

Since the context in which a question is asked may affect the survey results as well, ordering of items is also of significance. Krosnick and Presser (2010, p. 264) state that a good survey should take into account the following advice about how to optimise question order:

- Early questions are supposed to raise interest and to build rapport between the respondent and the researcher, why they should be easy and pleasant to answer
- Introductory questions should explicitly address the topic of the survey
- Questions on the same topic should be grouped together to facilitate memory retrieval and judgment formation
- Questions on the same topic should proceed from general to specific (i.e. a good questionnaire should implement the **funnel approach**)

Moreover, Lindell and Whitney (2001, p. 117 f.) posit that acquiescence can be reduced by reverse scoring some of the items. Hence, the developed questionnaire contains three reverse coded items ('IV01_02', 'PS02_04', 'PS02_06', and 'PS03_01') plus the reversed items of the Big Five personality traits (see chapter 6.3.1.1). Additionally, since socio-demographic items require relatively little cognitive processing, the authors recommend to place these items at the end of the questionnaire. This should reduce the respondents' susceptibility to response styles, peripheral cues and acquiescence due to an increasing fatigue when answering the questionnaire. To develop an understanding of the sample's structure and to assess the degree of representativeness of the sample, demographic items have thus been queried on the last page. Furthermore, Chang et al. (2010, p. 180) maintain that randomising the order of items would also make CMV less likely. This functionality is directly supported by the *SoSci Survey* software and, consequently, was also employed in the study. In sum, the overall questionnaire design reflects the well-accepted funnel approach, which is advised in (Churchill, et al., 2010 p. 220).

Even though all hypothetical constructs were operationalised and carefully translated into corresponding question items, a questionnaire is rarely flawless (Neelankavil, 2007, p. 184). Therefore, to eliminate design problems and to safeguard the quality of the questionnaire, a field-based pre-test should be performed with respect to the general design, wording and logical flow of the survey (MacKenzie & Podsakoff, 2012, p. 545; Malhotra & Grover, 1998, p. 412). Hence, prior to conducting the panel survey, the questionnaire was first submitted to the scrutiny of two experienced academics and two target respondents, who have been excluded from further participation thereafter. The survey software *SoSci Survey* provides a pre-test modus, whereby completed questionnaires can be viewed

and commented online via a password-protected access. During this process, both the question wording and the question sequence could be improved. To reach maximum comprehensibility, ambiguous terms (e.g. context-awareness or security risks such as hardware and software failures) were clarified by virtue of concrete examples. Also, to reduce potential fatigue and irritation of respondents, adjustments were made to some multi-item measures by eliminating ambiguous question items.

Overall, the pre-test provided positive feedback for the online questionnaire. After correction of the detected minor flaws, the survey instrument was finalised to go into the field. Following the first and second wave of the field phase, the collected data sets were directly exported from the online questionnaire into the software package IBM SPSS Statistics for statistical analysis. This automatism certainly reduces the risk of human error in the process of entering empirical data into a specialised evaluation software (Planing, 2014 p. 178). It should be noted that simple survey page visits (i.e. empty data records) were not considered by the survey software and, consequently, excluded from further statistical evaluation.

7.1.4 Data Preparation

Prior to any inferential statistical analysis, researchers should examine the quality of the collected data in respect of missing values, outliers, suspicious response patterns, and the normality of data distribution (Hair, et al., 2016 p. 56; Mooi, et al., 2011 p. 91 ff.). Moreover, since the dependent and independent variables in this study might be subject to CMV, statistical procedures should be used to examine the extent to which method bias may be a concern (Podsakoff, et al., 2003, p. 889). To prepare the primary data for analysis, identified invalid and suspicious cases have to be eliminated first. As the online questionnaire implements only fixed response options, outliers were not an issue for the present study. Moreover, with the aid of the chosen data collection software, all pages of the questionnaire were automatically checked for completeness during reply. In cases of incomplete pages, the users were directly informed about the respective missing responses by a pop-up dialog window when attempting to move to the next page. This setting together with the fact that this study employed a panel survey within the first wave ensured that nearly all data sets were complete.

Furthermore, atypical response patterns are problematic in terms of data quality. In particular, these anomalies may be observed by screening for data sets with a very high proportion of same responses (straight lining), such as 3,3,3,3,3 for each response option of a five-point multi-item scale. Within the collected data, no such case exists. However, respondents might also be uncommitted when they choose different ratings for the multiple items of a scale. Specifically, self-administration and panel structures might create incentives for completing a questionnaire quickly without expending the proper cognitive effort, what ultimately biases measurement results (Malhotra, 2008, p. 930). According to this, response times should additionally be taken into account as a *post hoc* data quality indicator for identifying inattentive or meaningless responses (Leiner, 2013, p. 10; DeSimone, et al., 2015, p. 173 f.). To this effect, *SoSci Survey* delivers a sophisticated approach, which relates the individual average response time per page with an index relative to the median page completion time of the entire sample. This indicator is normed in such way that values above 100 points suggest low-quality data, implying that the pages has been filled out five times as fast as the median response time of the sample (SoSci Survey GmbH, 2015; Leiner, 2013, p. 10).

A more conservative threshold has deliberately not been used in this study to eschew the risk of excluding very fast respondents. After applying this criterion on the gathered sample data, 19 data sets were excluded.

In addition, prior to distributing a questionnaire to the public, screening questions should be inserted to ensure that only those cases flow into the empirical assessment, which likely provide thoughtful responses (Hair, et al., 2016 p. 59; DeSimone, et al., 2015 p. 172). Hence, a reversed item ("Wearables are boring") in the introductory question at the beginning of the questionnaire served as a screening question to identify inconsistency in answers. Thereby, contradicting responses, which simultaneously indicate the same level of involvement and boredom towards the research object, have been excluded from further statistical analysis. Due to this quality control measure, 474 cases remained.

Furthermore, although PLS is a non-parametric method, extremely aberrant data may inflate standard errors and thus increase the likelihood of a false-negative error. Hair et al. (2016, p. 61) therefore suggest to assess both the **skewness** and **kurtosis** of parameter distributions. Instead of employing the prominent Kolmogorov/Smirnov and the Shapiro/Wilks tests, the authors particularly recommend using skewness and kurtosis statistics, since these measures are in line with the requirements of the PLS-algorithm (ibid.). Skewness indicates the extent to which a frequency curve is symmetrical, whereas the kurtosis indicates the 'peakedness' of a distribution. When both measures are close to zero, the data distribution is considered to be perfectly normal. The general guideline for skewness and kurtosis is that values below one or above minus one indicate univariate normality. However, in scholarly research this cut-off value is often considered to be too strict (Fraß, 2016, p. 202). Thus, literature even suggests absolute threshold values of 2.0 for skewness and 7.0 for kurtosis as moderate departures from a univariate normal distribution (Finch, et al., 1997, p. 91 f.). Skewness values for the Wearable TAM items range from -1.252 up to .559, and kurtosis values range from -1.176 up to 1.818, and, hence, fall under the recommended cut-off values. Since the given data is assessed as predominately normally distributed with only a few, not extremely non-normal cases, it can be regarded as fulfilling the distributional condition for the PLS algorithm.

Even though multiple *ex ante* measures have been implemented to reduce CMV (see sections 7.1.2, and 7.1.3), the existence of a method bias cannot safely be ruled out. *Harman's single-factor test* represents a widely used *ex post* exploratory procedure to address concerns regarding common method bias (Podsakoff, et al., 2003, p. 889). By loading all exogenous and endogenous variables of a research model into an EFA and assessing the unrotated factor solution, it can be established whether one factor accounts for the majority of the variance among the manifest measures. If this is the case, a substantial amount of common method variance is present. An EFA of all dependent and independent Wearable TAM variables results in a twelve-factor solution, with the first factor explaining about 30.9% of the variance in the data (cf. Table 7.1). Because the analysis yielded neither a single factor nor a general factor that accounts for the majority of the variance (i.e. more than 50%), Harman's test provides no evidence of substantial common method bias in this study. Still, it has to be emphasised that this test does nothing to statistically control for method effects; since this technique just indicates *significant* CMV in terms of a systematic measurement error, some problems due to a common source for predictor and criterion variables may persist.

COMPONENT	EXTRACTION SUMS OF SQUARED LOADINGS		
	Total	% of Variance	Cumulative %
1	17.929	30.911	30.911
2	5.579	9.619	40.530
3	3.785	6.525	47.055
4	2.636	4.545	51.600
5	2.531	4.363	55.963
6	1.889	3.257	59.221
7	1.684	2.903	62.124
8	1.483	2.556	64.680
9	1.294	2.231	66.910
10	1.219	2.102	69.012
11	1.146	1.975	70.987
12	1.083	1.867	72.854

Table 7.1: Extracted factors among the captured measures (unrotated factor solution)

7.1.5 Structure of the Survey Sample

This subchapter focusses on the crucial question if the data is truly representative of the target population of German wearable computing adopters. To get a sense of the properties of the drawn sample, the three characteristics 'gender', 'age', and 'educational level' has been used for describing the final survey sample composed of 474 respondents. As can be seen from Figure 7.1, the gender split was 57.00 % females and 43.00 % males. Since it has to be assumed that females are increasingly interested in consumer electronics (Moss, 2009, p. 37), this slight prevalence is considered acceptable. The results of the *Chi-square goodness-of-fit* (χ^2) test, which establishes whether an observed empirical distribution differs from a theoretical distribution, accordingly indicates with a value of χ^2 = 3,057 no sampling bias at a significance level of α = .001 when assessing the null hypothesis H_0 that there is no difference between the sample and the overall population (Lind, et al., 2006, p. p. 465 ff.).

In addition, Figure 7.1 gives an overview of the percentage share of age categories of the sample compared to the German population. The age distribution indicates that younger adults aged 20-29 were somewhat over-represented in comparison to German census statistics (Statistisches Bundesamt, 2017). From a supplier's point of view, this is clearly a worthwhile age group in terms of technology adoption behaviour at early stages of the product introduction process (Yun, 2013, p. 50). With particular regard to the elderly adults aged 50 and more, the overall age-profile of the sample corresponds largely to the target population. As opposed to other empirical studies where predominately students were surveyed (Fraß, 2016, p. 203), the present sample exhibits thus a more realistic spread of distribution of the relevant demographic characteristic. It has to be acknowledged in this context, that in the aging Western industrial populations various mobile health (mHealth) solutions are specifically designed to

assist older people with medical issues by means of body-worn sensors (Allen, 2016). An under-representation of elderly (which is frequently observable in studies on technology acceptance) would therefore result in a neglect of a promising future consumer market (Gartner, Inc., 2013b).

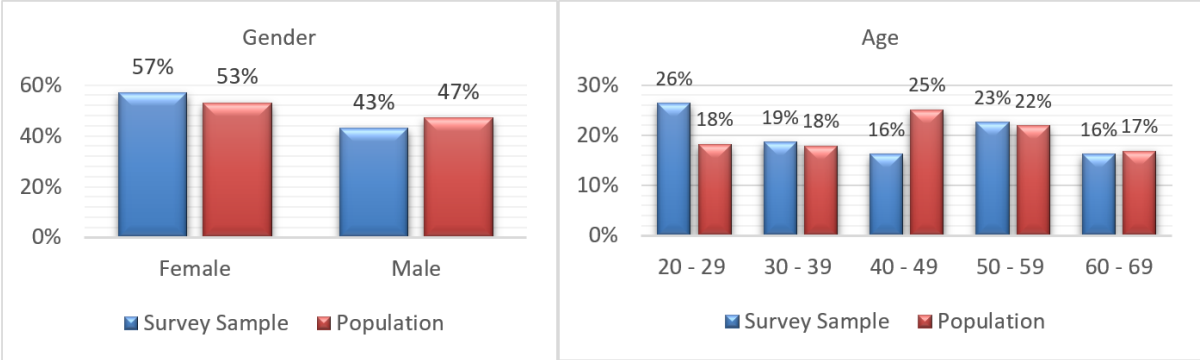

Figure 7.1: Comparison of gender and age distributions

Moreover, the direct comparison of age groups reveals that respondents aged 40-49 are clearly underrepresented. Thus, the sample is biased by too many youngest-group and too few middle-aged participants. As a consequence, the resulting summarised Chi-square ($\chi^2 = 33.483$) indicates that H_0 should be rejected. However, when looking at the other age categories individually (cf. Table 7.2), it becomes evident that most of them are representative of the target population: The acceptance region for the null hypothesis at a significance level of $\alpha = .01$ with 1 degree of freedom is below the critical value of 6.635 (Lind, et al., 2006, p. 494). Thus, more than half of the observed age categories of the sample can be judged as truly representative of the target population. Therefore, the overall targeting is viewed as being successful.

	20 - 29	30 - 39	40 - 49	50 - 59	60 - 69	Total
Observed	125	88	77	107	77	
Expected	86	84	120	104	80	
Difference	39	4	43	3	3	
χ2	*17,686*	*0,19*	*15,408*	*0,086*	*0,113*	*33,483*

Table 7.2: Chi-Square Goodness-of-Fit Test for age characteristics

Furthermore, the descriptive analysis shows that the educational level of the survey respondents can be regarded as far above-average; the distribution of the survey participants is clearly skewed towards better-educated (see Figure 7.2). Nearly 40% of respondents state that they hold a university degree, while 20% have a general qualification for university entrance. This group distribution corresponds well with the socio-economic structure of innovators and early adopters, who are considered to be generally more qualified (Yun, 2013, p. 91). Since there is no data on the population distribution of this characteristic available, no additional chi-squared test has been performed for educational level.

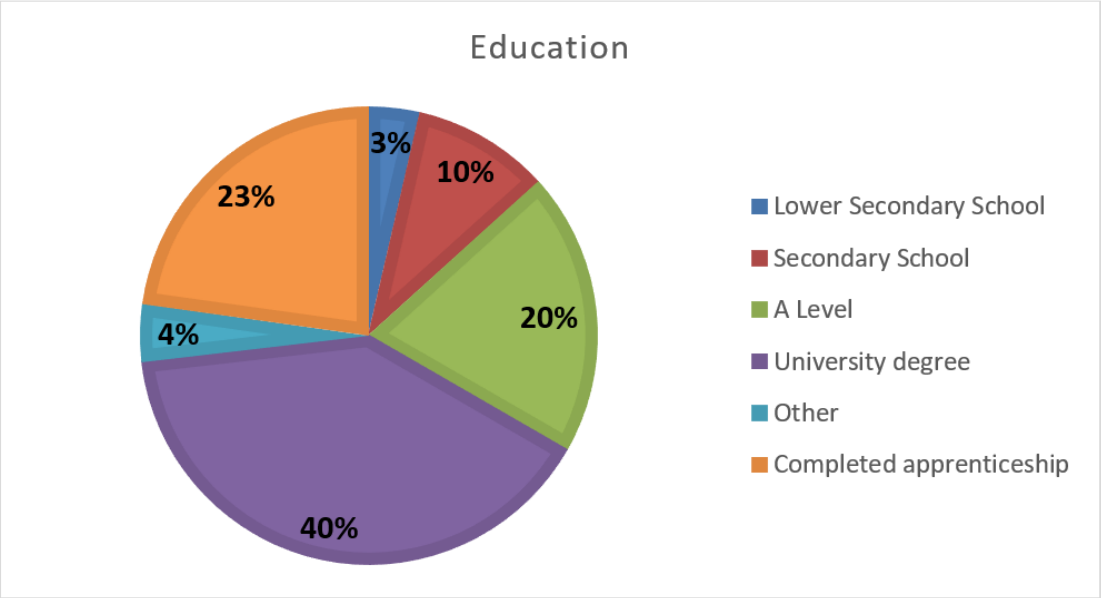

Figure 7.2: Distribution of respondent's educational level

With respect to the level of familiarity with wearable computing, the results suggest that the majority of respondents at least knows the term 'wearables'. This complies well with the relatively high educational level of the sample. Only 8% of participants have never heard of these new technologies before. The group distribution is made up as follows:

- Already very familiar with wearables -> 9.3%
- Know the concept basically -> 53.6%
- Have heard the term 'wearables' once before -> 28.7%
- Never heard of the term 'wearables' -> 8.4%

In a technology acceptance context, another revealing information concerning the structure of a sample population is the degree of personal innovativeness (Kim, et al., 2010, p. 314). Measures of central tendency (mean and median), dispersion (range, standard deviation, variation coefficient), and shape (skewness and kurtosis), which summarise the empirical frequency distribution of construct scores, may give a first impression of the occurrence of values within a group, and are hence a good starting point for further analysis (Chin, 2010 p. 671; Planing, 2014 p. 185). When assessing the descriptive statistical indices of the distribution of the external background factor 'personal innovativeness' (see Figure 7.3, which summarises distributional characteristics of the individual constructs scores through their quartiles), the sample median and upper quartile suggest a slightly above-average innovativeness of respondents. The empirical frequency patterns of categories approximate the bell-shaped adopter distribution curve postulated by Rogers in (1983, p. 245 ff.). Similarly, the sample distribution of prior experience with wearable devices shows that the survey participants tend to be well-acquainted with the concept of these new technologies.

	Innovativeness	Experience
Minimum	1,000	1,000
Maximum	7,000	5,000
1. Quartile	2,942	2,000
Median	4,002	4,000
3. Quartile	5,324	4,000
Mean	4,038	3,266
Standard Dev.	1,688	1,210
Skewness	-0,140	-0,491
Kurtosis	-0,796	-1,147

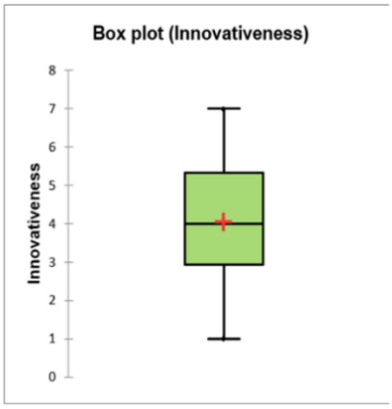

Figure 7.3: Descriptive statistics on innovativeness and past experience

In sum, the data structure shows a broad dispersion of socio-demographic values in the survey sample, what may be indicative of the generalisability of results. Both, the gender and the age distribution are essentially consistent with the German census statistics. In light of the conceptual sophistication of this research, it can be assumed that the predominance of better-educated participants does not tangibly influence the validity of statistical findings. Finally, aligning the difficulty of questions with the respondent's ability to link the key terms to the relevant concepts (e.g., as reflected in verbal skills and education) is an important means to diminish the likelihood of satisficing (MacKenzie & Podsakoff, 2012, p. 545). Taken together, it is expected that the chosen quota strategy in regard to income and educational level (see chapter 7.1.2) has reduced artifactual variance, which otherwise would have had a much stronger effect on the sample.

Besides possible sampling errors due to undercoverage problems, another threat to the external validity of study results is the *non-response bias*, which is fairly common in applied research settings (Churchill, et al., 2010 p. 328 ff.). The underlying assumption is that eligible persons who do not respond to a questionnaire may possess different characteristics. A method to check for the existence of non-response error is proposed by Armstrong and Overton in (1977, p. 396-402). Here, the fundamental idea is that individuals who respond late to a questionnaire tend to share characteristics with those who do not respond at all. Thus, the sample should be grouped by the answering date to compare early responses with late responses. The latter cluster is supposed to most closely resemble the characteristics of non-responding individuals. Since it is frequently believed that non-response bias is primarily indicative of socio-demographic differences (Roni, 2014, p. 31; Leslie, 1972, p. 323 ff.), the data collected in fieldwork t_1 and t_2 were individually clustered into two waves of early and late responses (roughly the first two-thirds and last one-third each) and a test was performed in regard to the age, gender, educational level, and past experience of the respondents. As can be seen from Table 7.3, the results of the Pearson's chi-square tests indicate no response bias for both the panel study t_1 and the subsequent Internet survey t_2. Considering the pertaining degrees of freedom, all $\chi 2$-statistics are below the required values, which is why no prove of response bias could be found for the four examined population characteristics.

	Age	Gender	Education	Experience
χ2 (t_1) (n_1 = 264; n_2 = 93)	3.390	.378	5.166	1.891
χ2 (t_2) (n_1 = 82; n_2 = 35)	5.154	2.135	4.171	1.216
Degrees of Freedom	4	1	5	3

Table 7.3: Pearson's Chi-Square test for demographic differences between early and late responses

Additionally, the three items 'AZ03_01', 'AZ03_02', and 'AZ03_03', which pertain to the *behavioural intention to adopt wearables* as the main criterion variable of this study, were tested for non-response errors. The obtained χ2-values range from 5,586 up to 7,685 for t_1 and from 2.071 up to 8.726 for t_2 with 6 degrees of freedom at α = .01 for each measurement scale. The presence of a non-response bias is therefore rejected for both study periods, indicating that the sample is sufficiently representative of the underlying population.

7.2 Empirical Purification of Measurement Models

As outlined in the preceding chapters, this work applies a two-step approach to test the derived causal model. In the first step, the psychometric properties of the latent constructs are evaluated to ensure adequacy of survey instruments. In the second step, the proposed correlative influence of the relevant users' traits and beliefs are assessed statistically to decide upon the confirmation or falsification of the theoretical hypotheses.

The model-inherent constructs were empirically tested for reliability and validity on the basis of the quality criteria discussed in chapter 6.2. The prepared and 'cleaned' data sets were then statistically evaluated by means of PLS-SEM with the software package SmartPLS in version 3.2.6 (SmartPLS GmbH, 2017). Given the Wearable TAM's structural complexity, the standard PLS-SEM algorithm was employed rather than PLSc. Taken together, the subsequent settings were applied for effectively performing the PLS analysis, including the bootstrapping and blindfolding procedure:

PLS algorithm

- Path Weighting Scheme
- Max. 300 Iterations
- Stop Criterion: 10^{-7}

Bootstrap procedure

- 3000 Bootstrapping Subsamples
- No Sign-Changes
- 0.05 Significance Level

Blindfolding procedure

- Omission Distance *D*: 7

7.2.1 Validation of Reflective Scales

To verify unidimensionality of measurement scales, in a first instance an EFA was conducted for all hypothesised constructs including the moderating variable of personal innovativeness. Because the other moderator (i.e. prior

experience with wearables) represents a single-item measure, it was excluded from outer model validation. Employing principal component extraction with varimax rotation, a one-dimensional factor structure could be affirmed for all latent variables, except the need for cognition scale. Here, the loading pattern of the *PS03_01* indicator led to the extraction of two components with each showing an eigenvalue greater than one. This heterogeneous item was therefore eliminated from further analysis, what resulted in a one-component solution for the remaining two-item-scale. The obtained empirical statistics for each question item are summarised in Table 7.4.

Afterwards, for all reflective indicators reliability was examined by computing the individual factor loading. Overall, the results indicate that the operationalised constructs prove reliable at item level; most factor loadings exceed the conservative threshold value of 0.7 and are also high of significance. Correspondingly, the same is true for AVE ratios which all surpass the 0.6 benchmark. However, the items *PS02_04*, *PS02_06*, *PS01_02*, and *PS01_05* fall clearly below the required λ-value. Following the recommendations in (Bagozzi, et al., 1991, p. 427 ff.) and (Hair, et al., 2011, p. 145 f.), rather than automatically eliminating weaker indicators from their theoretically associated reflective scale, in the present study the decision on item removal rested additionally upon plausibility considerations and a careful examination of the effects of a model adjustment on composite reliability. Because for the endogenous construct 'Materialism' item removal has led to a considerable increase in convergent validity, the respective indicator was dropped. In the case of *PS01_02* ('Agreeableness') and *PS01_05* ('Openness to Experience') indicator elimination resulted in single-item measures, why considerations on scale purification could not be based sensibly upon construct validity criteria. Therefore, Type I error probability of the concerning outer loadings was assessed. Here, one-tailed t-values are reported due to directional predictions. Since the loading of item *PS01_02* shows acceptable significance at a 0.01 level, it has been retained in the initial measurement model, whereas *PS01_05* had to be eliminated from further analysis due to its statistically insignificant loading on its assigned 'Openness to Experience' construct.

Moreover, when inspecting the matrix of loadings and cross-loadings, it becomes apparent that the items *AZ03_02* and *AZ03_03* pertaining to the usage intention as well as *IV01_03*, which measures the involvement towards wearables, exhibit substantial collinearity with lambda-values well above 0.7. Drawing on the tripartite model of attitude structure (see chapter 3.1.2.1), this may be explained by the fact that involvement reflects rather affective attitudinal facets of evaluative judgements. However, in accordance with the underlying theoretical and conceptual considerations, this study is supposed to explicitly analyse the singular effect of both behavioural intention and affective involvement at nomological level. Therefore, merging the problematic constructs into a more general higher-order structure was not an option. Even though all items load highest on their own construct with a delta above 0.1 compared to their cross-loadings as recommended by Gefen and Straub (2005, p. 93 f.), to establish discriminant validity all three problematic indicators were removed from their respective instruments.

Subsequently, reliability was assessed on construct level. For the endogenous latent variables, the postulated measurement models deliver very good results in terms of internal consistency. The Cronbach's alpha statistics exceed the minimum level of 0.6, while composite reliability values correspondingly meet the given benchmark of 0.7. Yet, with an alpha reliability of 0.410 for 'Conscientiousness' and 0.537 for 'Neuroticism', the exogenous personality scale shows relatively poor internal consistency. Nevertheless, given that Cronbach's alpha is a

conservative measure and that the true reliability usually lies between the Cronbach's alpha and the composite reliability score (which by contrast tends to overestimate internal consistency, c.f. Hair et al., 2016 p. 112), both criteria should be considered. As the latter first-generation criterion is fulfilled for the two sub-dimensions, both items were retained.

Latent Variable	**Item**	**Item Reliab.**	**Sign.**	**Internal Consistency Reliability**		**Convergent Validity**		**Discriminant Validity**	
		Loading	t-value	Cronb. Alpha	Comp. Reliab.	Eigen-value	AVE	Fornell-Larcker	HTMT
Unobtrusiveness	PV02_01	0.766***	21.119	0.897	0.924	3.547, .512	0.709	√ ($Corr_{max}$ = 0.523)	√ $HTMT_{max}$ = 0.573
	PV02_02	0.848***	48.857						
	PV02_03	0.874***	65.999						
	PV02_04	0.842***	39.680						
	PV02_05	0.875***	62.503						
Ubiquity	PV03_01	0.942***	113.44	0.967	0.974	4.418, .271	0.884	√ ($Corr_{max}$ = 0.726)	√ $HTMT_{max}$ = 0.771
	PV03_02	0.943***	100.58						
	PV03_03	0.944***	92.592						
	PV03_04	0.927***	78.566						
	PV03_05	0.945***	100.52						
Context Awareness	PV01_01	0.930***	118.12	0.906	0.941	2.526, .302	0.842	√ ($Corr_{max}$ = 0.679)	√ $HTMT_{max}$ = 0.725
	PV01_03	0.934***	115.85						
	PV01_04	0.889***	57.405						
Availability	NZ02_04	0.932***	121.25	0.915	0.946	2.565, .247	0.855	√ ($Corr_{max}$ = 0.706)	√ $HTMT_{max}$ = 0.775
	NZ02_05	0.912***	75.87						
	NZ02_06	0.930***	102.99						
Integrity	NZ06_01	0.912***	88.125	0.906	0.941	2.524, .268	0.841	√ ($Corr_{max}$ = 0.706)	√ $HTMT_{max}$ = 0.775
	NZ06_02	0.912***	78.207						
	NZ06_03	0.927***	97.804						
Confidentiality	NZ07_01	0.970***	218.71	0.973	0.983	2.848, .091	0.949	√ ($Corr_{max}$ = 0.649)	√ $HTMT_{max}$ = 0.690
	NZ07_02	0.974***	172.84						
	NZ07_03	0.979***	322.39						
Trust	NZ05_01	0.928***	113.09	0.918	0.948	2.579, .226	0.860	√ ($Corr_{max}$ = 0.774)	√ $HTMT_{max}$ = 0.771
	NZ05_02	0.923***	96.543						
	NZ05_03	0.931***	99.853						
	AZ03_01	0.960***	215.04	-[a]	-[a]	-[a]	-[a]	-[a]	-[a]

Latent Variable	Item	Item Reliab.	Sign.	Internal Consistency Reliability		Convergent Validity		Discriminant Validity	
		Loading	t-value	Cronb. Alpha	Comp. Reliab.	Eigen-value	AVE	Fornell-Larcker	HTMT
Behavioural Intention	*AZ03_02*	*0.950****	*196.64*						
	AZ03_03	*0.963****	*210.97*						
Involvement	IV01_01	0.933***	117.90	0.880	0.912	3.264, .406	0.804	√ ($Corr_{max}$ = 0.742)	√ $HTMT_{max}$ = 0.793
	IV01_02	0.826***	38.548						
	IV01_03	*0.944****	*138.73*						
	IV01_04	0.903***	70.942						
Materialism	*PS02_04*	*0.538****	*7.423*	0.868	0.919	2.777, .926	0.791	√ ($Corr_{max}$ = 0.333)	√ $HTMT_{max}$ = 0.374
	PS02_05	0.839***	38.639						
	PS02_06	*0.427****	*5.237*						
	PS02_07	0.902***	96.305						
	PS02_08	0.876***	72.022						
Innovativeness	ZS05_01	0.953***	193.39	0.918	0.918	3.175, .217	0.860	√ ($Corr_{max}$ = 0.716)	√ $HTMT_{max}$ = 0.705
	ZS05_02	0.928***	139.67						
	ZS05_03	0.899***	82.07						
Need for Cognition	*PS03_01*	*0.129*	*0.628*	0.791	0.903	1.655, .345	0.824	√ ($Corr_{max}$ = 0.281)	√ $HTMT_{max}$ = 0.390
	PS03_02	0.935***	76.392						
	PS03_03	0.846***	35.984						
Neuroticism	PS01_04	0.729***	9.410	0.537	0.804	1.367, .633	0.675	√ ($Corr_{max}$ = -0.394)	√ $HTMT_{max}$ = 0.648
	PS01_09	0.904***	23.062						
Agreeableness	*PS01_02*	*0.046*	*0.587*	-[a]	-[a]	-[a]	-[a]	-[a]	-[a]
	PS01_07	0.992***	4.064						
Openness to Experience	*PS01_05*	*0.468****	*2.070*	-[a]	-[a]	-[a]	-[a]	-[a]	-[a]
	PS01_10	0.988***	11.392						
Extraversion	PS01_01	0.847***	19.924	0.663	0.855	1.496, .504	0.747	√ ($Corr_{max}$ = -0.357)	√ $HTMT_{max}$ = 0.549
	PS01_06	0.882***	29.607						
Conscientiousness	PS01_03	0.800***	5.956	0.410	0.772	1.177, .823	0.629	√ ($Corr_{max}$ = -0.394)	√ $HTMT_{max}$ = 0.793
	PS01_08	0.785***	6.082						

Notes: -[a] The construct is measured with one item. Internal consistency, convergent validity, and discriminant validity cannot be appropriately computed; Significance Level *p≤0.1; **p≤0.05; ***p≤0.01 (one-sided)

Table 7.4: Assessment of reflective scales

Finally, having determined convergent validity of constructs, discriminant validity was evaluated for all reflective measurement models. Results of both the Fornell-Larcker criterion and the HTMT test clearly speak in favour of empirically distinct constructs. In addition to assessing the HTMT statistic, the author tested whether the HTMT values are significantly different from 1 by computing **bootstrap confidence intervals** as advised by Henseler et al. (2015, p. 122). The confidence interval gives the range within which the true population parameter will fall assuming a certain level of confidence. Because the bias-corrected confidence interval in-between the 2.5% lower bound and the 97.5% upper bound does not include the value 1, discriminant validity is supported. To sum up, measurement models are thus of satisfactory quality as regards reliability and validity of constructs.

7.2.2 Validation of Formative Scales

Product-related characteristics including usefulness dimensions, IT security risks, and pervasiveness facets are aggregated into formatively measured model constructs. As outlined in chapter 6.2.5, formative indicators do not necessarily have to be intercorrelated as is the case for reflective items. Therefore, composite indicators must not be purified due to correlation patterns and, moreover, only a reduced subset of criteria is applicable for validating a formative measurement model's quality.

Firstly, under a formative measurement scheme content validity has to be ensured in respect of completeness of the focal construct's constituting facets as defined by the researcher. This was already done by drawing on appropriate established and validated scales from prior research in the conceptual part in Chapter 6.3.1.3. To address concerns of potential collinearity among block indicators, the VIF-values were then assessed. For this purpose, each composite indicator of the 'Perceived Usefulness' construct (*NZ04_01 – NZ04_05*) as well as the computed first-order construct scores of 'Perceived IT Security Risks' (*LOC_Confidentiality*, *LOC_Integrity*, and *LOC_Availability*) and 'Perceived Pervasiveness' (*LOC_Ubiquity*, *LOC_Context_Awareness*, and *LOC_Unobtrusiveness*) were regressed alternately on all remaining measures of their respective block to obtain tolerance statistics. An overview of the final statistical figures is given in Table 7.5.

Construct	Indicator	Outer weight	t-value	Outer loading	VIF
Perceived Usefulness	NZ04_01	0.372***	5.305	0.925	3.368
	NZ04_02	0.428***	6.927	0.927	2.916
	NZ04_03	-0.005	0.065	0.800	3.690
	NZ04_04	0.192**	2.530	0.856	3.380
	NZ04_05	0.138**	2.491	0.718	2.438
Perceived Pervasiveness	LOC_Ubiquity	0.492***	6.320	0.894	1.977
	LOC_Context_Awareness	0.335***	3.832	0.839	1.944
	LOC_Unobtrusiveness	0.369***	5.852	0.756	1.351

Construct	Indicator	Outer weight	t-value	Outer loading	VIF
Perceived IT Security	LOC_Confidentiality	0.687***	4.834	0.946	1.732
	LOC_Integrity	0.495**	2.687	0.851	2.633
	LOC_Availability	-0.126	0.752	0.558	2.000
Significance Level *p≤0.1; **p≤0.05; ***p≤0.01 (two-sided)					

Table 7.5: Assessment of formative scales

As per empirical results, pairwise linear dependency of indicators does not reach critical levels in any of the formative scales. VIF-statistics range between 3.690 and 1.351 and are thus uniformly below the recommended cut-off value of 5.0.

Since no substantial collinearity issues exist, next, the significance and relevance of outer weights have to be assessed. Therefore, the bootstrap re-sampling procedure was conducted, so that every indicator´s outer weight (**relative importance**) could be analysed with regard to its significance. The t-values suggest that all weights, with two exceptions, are significant on an α 0.05 level. Only *NZ04_03* and *LOC_Availability* fail with a t-value of 0.065 and 0.752. Correspondingly, the relative contribution to their assigned constructs is of minor importance, exhibiting even reversed weight signs, which are hardly interpretable. Nonetheless, it should be reiterated that also small interaction effects among formative measures may cause biased estimates and suppressor effects. When assessing the magnitude of correlation between the negatively weighted variables concerned (*NZ04_03* and *LOC_Availability*) and the other predictors of the same formative block and between the negatively weighted variables and their regression criterion (i.e. construct), it becomes evident that crucial correlation patterns among the measures are present, violating the independence hypothesis of the classical regression model.

In the case of *NZ04_03*, the VIF-value provide indication that there is indeed a technically problematic level of collinearity; almost 73% of variance of this indicator are explained by the other formative items. Additional analyses revealed that there is no suppressor effect involved in the model but rather a confounding third variable effect as implied by the tolerance statistic. Notably, removing this indicator from its battery does not change the multiple determination index (R^2) of the 'Perceived Usefulness' scale, since the regression coefficients of the other indicators are not suppressed by the item *NZ04_03*, et vice versa. In the event of nonsignificant indicator weights, Hair et al. (2017, p. 147) propose to consider the **absolute contribution** of the respective manifest measures to their associated index. The authors content that Lambda-values should be ≥ 0.5 to be indicative of the factors' usefulness in prediction. Due to its high outer loading ($\lambda = 0.8$), this formative indicator was thus retained in the measurement model.

On the contrary, further analyses showed that *LOC_ Integrity* is actually acting as a suppressor variable on *LOC_Availability*. The latter variable positively correlates with the suppressor and the dependent variable but at the same time, paradoxically, receives a negatively weighted beta coefficient. Suppression can be detected by comparing the effect of an independent variable X on a criterion variable Y in two regression models, one predicting Y from only the X variable, the other predicting Y from both the X variable and the confounding third

variable (MacKinnon, et al., 2000, p. 175). Within an inconsistent mediation model, a negative suppression effect would be present if the bivariate and multivariate regression effect of X on Y have opposite signs or if the bivariate effect is significantly larger than the multivariate regression effect, respectively. Consequently, the (negative) suppression phenomenon is usually reflected by situations where the independent and the third variable appear jointly to explain less variation in the criterion variable than they uniquely do.

To investigate the suppressor effect, the two variables *LOC_Integrity* and *LOC_Confidentiality* were thus alternately removed from the higher-order measurement model of perceived security risk. Specifically, it was found that *LOC_Integrity* must be present in the model to provoke the suppressor impact. Including this indicator results in a reduction of availability β from 0.54 to 0.351. From a technical perspective, *LOC_Availability* shares less variance with its construct than with this indicator (r = 0.706); when both independent variables are included in the multiple regression equation, *LOC_Integrity* suppresses thus a part of *LOC_Availability*'s information. Hence, the two risk facets are conceptually and empirically interrelated as manifested in the inconsistent mediation model Availability → Integrity → Confidentiality. This seems plausible, because systems which are perceived as being unreliable are more likely to be expected as malfunctioning and causing data corruption. Parallelising the concept of perceived security risk with the traditional framework of technology trust (consisting of the sub-dimensions 'ability', 'benevolence', and 'integrity', see chapter 3.2.2), it becomes clear that both availability and integrity refer to the system's functionality at technical level, whereas confidentiality rather relates to the benevolence of the involved service providers and possible third-parties.

As a result, omitting the variable *LOC_Availability* from the security risk scale leads to a slight decrease in the R^2 (from 0.129 to 0.128) due to the spurious relationship. Yet, the indicator's outer loading is above 0.5, what can be regarded as sufficiently acceptable. Moreover, Cenfetelli and Bassellier (2009, p. 697) recommend that if „negatively weighted items are (a) not suppressors or (b) not collinear, they should be included in the remaining analysis and potentially culled over time if they repeatedly behave differently than other indicators […]". Since collinearity is not an issue in regard of the generated VIF-values and taking into account the theoretical and conceptual support, the perceived IT security risk scale was not purified, either.

7.3 Evaluation of the Structural Model

Once the hypothesised constructs are confirmed to be reliable, the structural model results should be evaluated. In response to the research question concerning the empirical impact of the identified acceptance factors, the next step was therefore to embed these constructs into an integrative cause-and-effect model (i.e. the Wearable TAM) and to assess the nomological validity of the formulated hypotheses. Thus, this chapter concentrates on a preliminary corroboration or, where necessary, falsification of the derived causal statements according to the key criteria described in section 6.2.6. Under consideration of the two model-inherent higher-order constructs 'Perceived Pervasiveness' and 'Perceived IT Security Risk', the path weighting scheme was chosen for performing the parameter estimates. The following sections briefly outline the path-analytical results. A more detailed and advanced discussion on the most relevant findings is given in chapter 7.4.

First of all, analogous to the formative index construction in subchapter 7.2.2, to avoid deflated path coefficients possible collinearity among model-inherent latent variables should be detected before testing the inner model (Hair, et al., 2016 p. 192). Therefore, the variance inflation statistics for the structural model were assessed first. Since the highest resultant inner VIF-value amounts to 2.895 and hence turns out to be considerably below 5.0, the model can be regarded as bearing no critical multicollinearity. The key results of the performed PLS-SEM algorithm are shown in Table 7.6.

Endogenous Construct	**Predictor**	**VIF**
Intention to Use	Perceived Usefulness	3.225
	Perceived Pervasiveness	2.838
	Perceived Security Risk	1.163
	Trust in Wearables	3.364
	Involvement	2.659
Involvement	Need for Materialism	1.000
	Need for Cognition	1.000
Need for Cognition	Conscientiousness	1.110
	Extraversion	1.209
	Openness to Experience	1.100
Need for Materialism	Agreeableness	1.025
	Neuroticism	1.025

Table 7.6: Multicollinearity diagnostics coefficients at structural model level

The effect of the postulated predictor constructs on the intention to use wearables was measured by examining the standardised beta coefficients obtained from the multiple regression, so the magnitude and sign of path coefficients can be interpreted in regard to the strength and direction of the formulated structural relationships. Figure 7.4 displays the structural model. The effects are visualised as arrow paths and the strength and significance of the pertaining structural coefficients (β) is given for each hypothesised relationship. In addition, R-squared values, which indicate the portion of a dependent variable's explained variance, and the Stone-Geisser's Q^2-test criterion as a measure for the predictive relevance of a reflective regressand are reported. Non-significant relationships are illustrated by dotted lines. As shown, most of the obtained structural parameters suggest strong empirical relations by means of the produced path coefficients. Correspondingly, the estimated Q^2-values above 0.0 indicate predictive relevance of the model equations. Only the proposed dependency structures denoted by H_3, H_4, and H_9 fail to meet the established requirement level ($\beta > 0.1$). To verify the significance of the hypothesised causal links, two-tailed t-tests were used due to the bidirectional nature of the nomological net (i.e. some hypotheses such as H_2 and H_{3a} operate in opposite direction). Again, all three hypotheses H_3, H_4, and H_9 can be considered as being not supported by the data, since the error probability for the respective path coefficients is greater than 0.1. Moreover, the effect sizes of the concerning predictor constructs (i.e. 'Conscientiousness', 'Perceived

Pervasiveness' and 'Trust in Wearables') on their related dependent variables (i.e. 'Need for Cognition' and 'Behavioural Intention to Use') indicate a substantively meaningless explanatory contribution, having f^2-values far below 0.02 (cf. Table 7.8). In light of the estimation results, hypotheses H_3, H_4, and H_9 have to be rejected. In this context, it is shown in subchapter 7.3.1 that both pervasiveness perceptions and affect-based trust are rather mediated by their theoretically linked cognitive technology beliefs. Since all other relationships in the base model are significant at a 0.05 level and above, the respective hypotheses are corroborated.

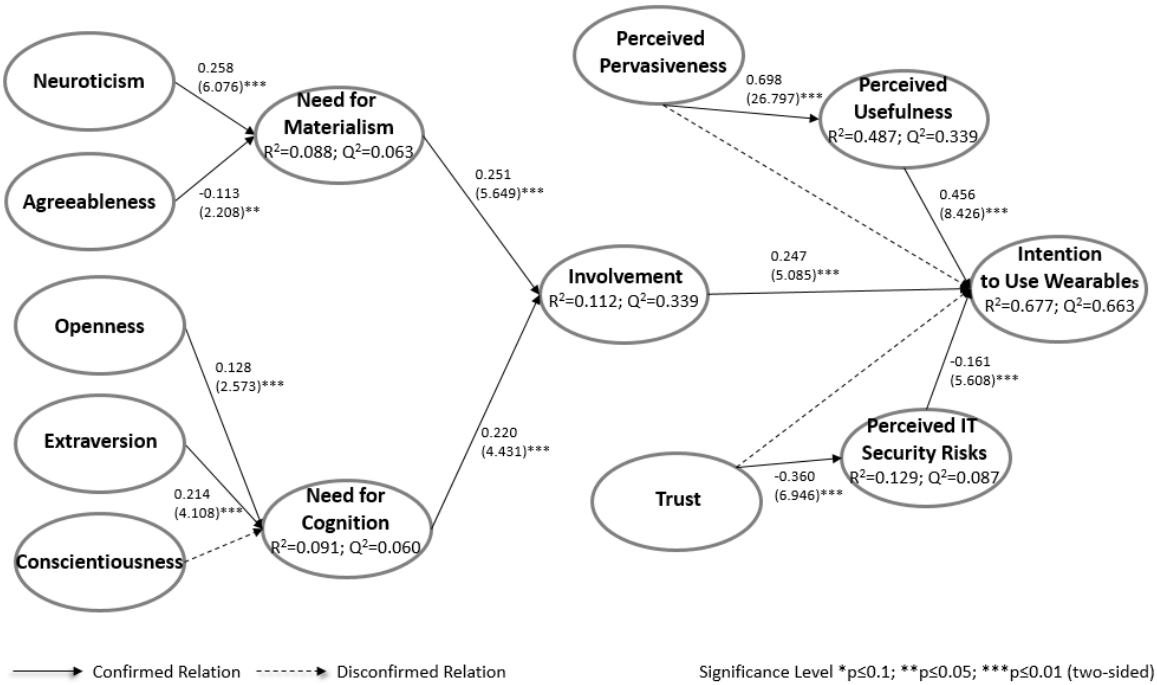

Figure 7.4: Path coefficients, significance values and predictive capacity of the integrative structural model

The explanatory competency of the inner structural model is judged by determining the R^2-value of each endogenous latent variable. In respect of the present epistemic goal of explaining the interpersonal attitude formation in wearable computing markets, a substantial determination coefficient should be targeted for the dependent criterion variable *Behavioural Intention to Use Wearables*. As can be seen from Table 7.7, the estimated attitudinal model fits the survey data well, with an R^2 of 0.677. The in-sample predictive power of the other endogenous constructs *Perceived Usefulness*, *Perceived IT Security Risk*, and *Involvement towards Wearables* is essentially evidenced by determination coefficients above the critical value of 0.1. Contrarily, less than 10% of the variance of both personality factors *Materialism* and *Need for Cognition* is accounted for by means of the Big Five elemental traits. Given the multifaceted nature of personality-related predispositions and the fact that even R^2-values between 0.05 and 0.1 could be considered a 'good' fit in social science (Thorne & Giesen, 2003, p. 314), the low squared correlation between the two compound traits and their assigned elemental traits is regarded as acceptable for the present study purposes. Complementary to the resulting R^2-values, Table 7.7 lists the **adjusted coefficient of determination** criterion R^2_{adj}, which reduces the R^2-statistic by the number of predictors and the sample size (Hair, et al., 2016 p. 199). Since the number of explaining constructs hardly varies among the model-inherent endogenous variables, both measures of the correlational framework's predictive power differ only marginally.

Endogenous Construct	Coefficient R^2	Coefficient R^2_{adj}	Stone-Geissers Q^2
Behavioural Intention	0.677	0.674	0.663
Perceived Usefulness	0.487	0.486	0.339
Perceived IT Security Risks	0.129	0.127	0.087
Involvement	0.112	0.108	0.081
Materialism	0.088	0.084	0.063
Need for Cognition	0.091	0.085	0.060

Table 7.7: Multiple determination coefficients and Q^2-statistics of the latent endogenous Wearable TAM constructs

In addition to assessing the multiple determination coefficients of the dependent latent variables, the substantive impact of the associated exogenous constructs should be evaluated (see Table 7.8). Consistent with the findings on the predictive power of the endogenous variables, the f^2-values of the Big Five personality dimensions indicate small effects. It can be concluded from these results that other external third variables are accounting for a substantial portion of variance in the compound level personality variables. However, since this study does not aim at fully explaining relevant latent traits but rather seeks to explore the individual effect of well-recognised personality domains in a wearable computing adoption context, the uninformative causal links render not problematic from an epistemic perspective. When looking at the direct effects on the base models' cognitive variables, it becomes evident that the predecessing technology beliefs possess significant predictive power. Especially the high f^2-value for *Perceived Pervasiveness* may indicate the predictive capacity of the path model as regards the attitudinal structures.

Exogenous Construct	Endogenous Construct	Effect Size f^2
Perceived Usefulness	Behavioural Intention	0.326
Perceived Pervasiveness	Perceived Usefulness	0.951
Perceived Pervasiveness	Behavioural Intention	0.004
Perceived IT Security Risks	Behavioural Intention	0.083
Trust in Wearables	Perceived IT Security Risks	0.148
Trust in Wearables	Behavioural Intention	0.003
Involvement	Behavioural Intention	0.101
Materialism	Involvement	0.071
Need for Cognition	Involvement	0.055
Neuroticism	Materialism	0.071
Agreeableness	Materialism	0.014
Openness to Experience	Need for Cognition	0.016

Exogenous Construct	Endogenous Construct	Effect Size f^2
Extraversion	Need for Cognition	0.041
Conscientiousness	Need for Cognition	0.003

Table 7.8: Effect sizes of exogenous constructs

The final assessment of the structural equation model addresses the **predictive relevance** of the reflectively measured, endogenous constructs. This criterion is assessed with the help of Stone-Geisser Q^2, which is calculated by means of the blindfolding procedure. As the resulting Q^2-values for all reflectively measured dependent variables are positive (cf. Table 7.7), sufficient predictive relevance of the path model can be assumed. What is more, given that Q^2 effect sizes of 0.02, 0.15, and 0.35 indicate that an endogenous construct has a small, medium, or large predictive relevance, respectively (Hair, et al., 2016 p. 208), the proposed path model demonstrates out-of-sample predictive power for the dependent criterion variable of wearable computing acceptance. The endogenous variables *Perceived Usefulness* and *Perceived IT Security Risk* are specified as formative first and second-order constructs. For this reason, Q^2 is not interpretable for both constructs.

Overall, based on the above discussed second generation quality criteria, the developed cause-and-effect model indicates that both personality structures and cognitive beliefs (i.e. subjective benefit and cost expectations) exert significant total effects on the decision to adopt wearable technologies. The magnitude and statistical significance of parameter estimates together with the obtained determination coefficients and the demonstrated predictive validity of model constructs clearly underline the importance of attitudinally-relevant value perceptions and predispositions in a ubiquitous computing setting. In particular, the PLS estimation results highlight the utmost important role usefulness perceptions play in intention formation processes. In line with the apriorically defined conceptual framework, the felt pervasiveness of wearables is completely mediated by utilitarian considerations. On the contrary, the hypothesised relationship between conscientiousness and the tendency to engage in cognitive tasks is not supported by the empirical data. Aside from this, both drivers of benefit and cost perceptions (i.e. the perceived pervasiveness and trust towards wearables) do not show a significant association to the target construct. However, their effect on usage intention is largely intervened by cognitive dimensions of attitude and, thus, of indirect nature, as will be shown hereafter. In conclusion, quantitative evidence for the nomological validity of the conceptualised structural model is found since the relevant quality standards are fulfilled. Yet, prior to conclusively accepting and interpreting these findings, the next sections examine further interacting effects pertinent to the causal model.

7.3.1 Mediating Effects

Overall, the developed nomological net implies two indirect relationships among the attitude-forming constructs. Such interdependencies, which are directed towards an endogenous variable by means of an intermediate element, are referred to as 'mediating effects' in structural equation research (see chapter 6.2.6.2). Within a PLS-SEM path model, mediator variables are directly implemented and their effects are automatically considered. However, the resulting parameters do not readily permit an evaluation of the character and magnitude of mediating effects.

Therefore, to determine the type of mediation, the partial structures of both three-variable systems have to be analysed separately.

With the working hypothesises H_{3a} and H_{4a} the designed conceptual framework focusses on the two mediating variables *Perceived Usefulness* and *Perceived IT Security Risks*. Testing for the character of the mediational relationships was based on an assessment of the significance of the indirect effects in a first step to rule out possible nonmediation. If the indirect effects render statistically significant, the error probability of the direct relations can be analysed in a second step. As in the course of the inner model evaluation, the significance levels of the mediation models were calculated by applying two-tailed t-tests using 3000 bootstrap samples and the individual sign changes option as recommended by Hair et al. in (2017, p. 239). Table 7.9 summarises the statistical findings.

Mediated Relationship	**Indirect Effect of Exogenous Variable (Indirect Pathways)**	**Main Effect of Exogenous Variable**		**VAF**
		Mediator Inclusion	**Mediator Exclusion**	
Pervasiveness → Usefulness → Intention	0.318 (8.145)***	0.064 (1.370)	0.129 (2.490)**	83.25%
Trust → IT Security Risks → Intention	0.058 (4.189)***	0.060 (1.255)	0.278 (5.485)***	49.15%
Notes: t-values of pathways in brackets; significance level *p≤0.1; **p≤0.05; ***p≤0.01 (two-sided)				

Table 7.9: Effects of mediated relationships

The results from the pseudo-population indicate that both indirect pathways as denoted by H_{3a} and H_{4a} are significant at an alpha 0.01 level. It can therefore be concluded that a mediating effect is present in either causal relationship.

Moreover, further mediation analysis revealed that the intermediate constructs account to a large extent for the total effects of the endogenous variables in both mediation models. Table 7.9 contrasts the results of the partial models with and without the mediator variables. When controlling the usefulness variable, the main effect of *Perceived Pervasiveness* increases from $\beta = 0.064$ to 0.129 and becomes satisfactorily significant at a 0.05 level. Thus, it may be assumed that the influence of *Perceived Pervasiveness* is completely transmitted through the mediator *Perceived Usefulness*. Accordingly, the VAF-value .8325 suggests a full mediation, where the mediator variable explains more than 83% of the total effect of *Perceived Pervasiveness* and, therefore, entirely complies with the hypothesised theoretical framework.

Similarly, when controlling the *Perceived IT Security Risk* variable, the direct pathway from *Trust* to the *Behavioural Intent to Use Wearables* becomes significant at a 0.01 level. According to Nitzl et al. (2016, p. 15), these findings meet the criteria for a full mediation model, as the endogenous construct *Trust* extracts its influence on the criterion variable only under the condition that the mediating mechanism is included into the model. However, since only 49.15% of the total effect are accounted for by the mediated relationship, the results may point to an incomplete theoretical framework. It can be expected therefrom that there likely exists another mediating variable which potentially explains a greater share of the causal relationship between *Trust* and

Behavioural Intent to Use. In sum, the results show that a partial mediation is present in the submodel, whereby the *Perceived IT Security Risk* variable plays a significant mediating role for trusting beliefs in an IT adoption decision context. Further research is certainly needed to elaborate these findings.

7.3.2 Moderating Effects

Since it is often unrealistic that empirical data originate from a single homogeneous population, in SEM literature it is generally recommended to account for potential segment-level heterogeneity by identifying *a priori* segments when applying multivariate analysis methodologies in Information Systems disciplines (Ringle, et al., 2010, p. 19; Herrmann, et al., 2002, p. 243 ff.). As discussed in chapter 5.3, the apriorically identified moderator variables 'Innovativeness' and 'Past Experience' are expected to influence the strength of the dependency structures of the cognitive attitudinal components *Perceived Usefulness* and *Perceived IT Security Risk*, which were found to significantly affect the decision to adopt wearables. Since both predictor constructs have a formative measurement model and, moreover, both moderators are metrically-scaled, the two-stage approach is technically appropriate for analysing the hypothesised interaction effects (Henseler & Chin, 2010, p. 86). Notably, this study assumes that the construct measures are invariant across the subsamples, i.e. the moderator variable's effect does not entail segment-related differences in the item loadings (Sarstedt, et al., 2011, p. 199). The performed moderation analyses of the influence of the control variables on the relationships between conative attitude and cognitive risk-benefit perceptions thus followed a sequential latent variable score method for creating the interaction term. The indicators of the main and interacting variables were standardised (by having a mean of zero and a standard deviation of one) in order to ensure sensibly interpretable regression estimates and effect sizes (Chin, et al., 2003, p. 195 f.). It is worth noticing that the calculated interaction term tends to yield low correlations due to the reuse of indicators (ibid.). To avoid confounding effects, the moderator models were examined individually. The results for the multivariate regression models that incorporate the interaction terms are given in Table 7.10.

Interaction Term	Path Coefficient	t-Value	Effect Size f^2
Innovativeness * Usefulness	0.066	3.337***	0.018
Innovativeness * Risk	-0.035	1.591	0.005
Experience * Usefulness	0.076	3.301***	0.021
Experience * Risk	-0.019	6.220***	0.001
Significance Level *p≤0.1; **p≤0.05; ***p≤0.01 (two-sided)			

Table 7.10: Effects of moderated relationships

After having assessed the psychometric properties of the 'Innovativeness' construct's measurement model (i.e. its reliability and validity, see chapter 7.2.1), statistical significance of the model-inherent interaction effect *Innovativeness*Perceived Usefulness* was examined using the bootstrapping procedure. The findings clearly support the moderator hypothesis, postulating that the level of personal innovativeness systematically amplifies the positive correlation between *Perceived Usefulness* and the *Intention to Use Wearables*; the beta coefficient of the interaction term amounting to 0.066 is at a 0.01 level significant. Similarly, the 95% bias-corrected bootstrap

confidence interval does not include zero. Jointly, these results suggest that holding all other standardised predictors constant, for higher levels of personal innovativeness (i.e. the mean value of innovativeness is increased by one standard deviation unit), the simple effect between *Perceived Usefulness* and *Usage Intention* increases by the magnitude of the interaction term, i.e. by 0.066. According to Kenny (2015), the estimated effect size (f^2 = 0.018) of the moderating model certifies a medium confounding effect (cf. chapter 6.2.6.1). Thus, the inclusion of the interaction variable into the multiple equation system provides a valuable contribution to the understanding of behavioural differences in innovative population segments.

Likewise, familiarity with wearable computers strongly affects the relation between usefulness perceptions and usage intentions. The discrepancy of the effect of *Perceived Usefulness* in experienced and unexperienced cohorts is expressed by a path coefficient of 0.076. Thus, the effect of usefulness perceptions changes to a beta coefficient of 0.532 when the level of past experience with wearables is increased by one standard deviation. In addition, the structural parameter of the interaction term is significant with an error probability of $p < 0.01$; also, the bias-corrected confidence interval is positive. Furthermore, the f^2-value 0.021 justifies *a posteriori* the inclusion of the moderator construct into the path model. It can be concluded therefrom that the background variable *Past Experience* substantially contributes to the clarification of the variance in responses with regard to the treatment group. The key figures thus support both moderator hypothesises H_{M1} and H_{M3}.

On the contrary, the effect of personal innovativeness on the causal association between *Perceived IT Security Risk* and behavioural intention renders not significant with a t-value below 1.6. Even though the pathway runs in the hypothesised direction, its beta coefficient of -0.035 provides only a trivial explanatory contribution. In line with this result, the moderated regression effect size of 0.005 gives evidence of rather marginal differences among innovative segments with regard to their intention formation. Therefore, hypothesis H_{M2} has to be rejected. By way of contrast, the interaction term *Experience*Usefulness* indicates a statistically significant negative moderating relationship with a Type I error probability below 0.01. However, the f^2-value falls under the recommended minimum level of 0.005 and hence suggests a substantively meaningless hypothesised effect that is rather uninformative. For this reason, the moderator hypothesis H_{M4} has to be dismissed, too.

In sum, the moderation analysis leads to the conclusion that the structural relation between *Perceived Usefulness* and *Behavioural Intention to Use Wearables* is strongly moderated by innovativeness and prior experience with wearable technologies. On the contrary, no effect of either conceptualised moderator variable could be proven for the perceived risk → intention relationship. Hence, further interacting third variables may be assumed, which account for the variability in response patterns when it comes to risky adoption decisions.

7.3.3 Multigroup Analysis

Heterogeneity in data structures is endemic in social sciences, whilst aggregate analysis results can be seriously fallacious when there are significant differences between subsample-specific parameters (Ringle, et al., 2010, p. 22). Therefore, in addition to the previous moderation analysis the present study employed a multigroup analysis, which focussed on the most salient consumer demographics in behavioural sciences. A multigroup comparison is a kind of moderator analysis, where typically categorial data such as gender are hypothesised to manifest in

different modalities in a population parameter θ across different segment-specific subpopulations (e.g. $\theta^{(1)}$ in group one and $\theta^{(2)}$ in group two).

The **nonparametric multigroup analysis** (PLS-MGA) approach tests for group differences by comparing bootstrap estimates for each population parameter (Henseler, 2012 p. 495 ff.; Hair, et al., 2016 p. 294). The corresponding null-hypothesis is that there is no difference between the two groups under investigation. By accumulating the number of occurrences where the difference between the distinct groups is sufficiently large, the procedure derives a probability value. A significant difference in group-specific path coefficients on a 5% level is given, if p-values are above 0.95 or below 0.05. Also, only empirically meaningful paths should be accepted, so the minimum β-threshold of 0.1 shall be applied (Fraß, 2016, p. 234). According to Chin (2000), pairwise t-tests require that the collected data should not be too skewed, each sub-model must be valid in terms of the standard PLS evaluation criteria, and that there should be measurement invariance. In the context of this study, the former two assumptions are met as discussed above. Because all indicators per measurement model as well as data treatment and algorithm setting were identical for the specified groups, configural measurement invariance can be expected, too (Milfont, et al., 2010 p. 115). Since the PLS-MGA algorithm has recently been implemented in SmartPLS 3.0, multigroup comparisons could be directly performed.

Due to the high number of integrated effect relationships and the resulting complexity of the research model, only the most salient demographic characteristics were considered. More specifically, for the present moderator analysis the control variables gender, age, and education background were used to establish subsamples. For each of the two latter grouping variables the sample was dichotomised to meet the requirements of PLS-MGA and to arrive at more general, aggregated path estimators which allow for more manageable results. In order to enable an interpretation of the differences in effects between younger and older sample units, segments were established on the basis of a median split. As shown in the following, considering adopter diversity in terms of generational cohorts is also important, which is why an additional segment were introduced for analysis. For the educational level, on the contrary, the dummy coded moderator variable 'education' dichotomises the sample into participants, who have passed their A-Level or hold a university degree, and all other participants with a lower educational level. The resulting groups are presented in Table 7.11.

Gender		**Age**		**Educational Level**		**Generational Cohort**	
Group	*n*	*Group*	*n*	*Group*	*n*	*Group*	*n*
Male	204	<= 39	213	Higher-Educated	284	Digital Natives	125
Female	270	>=40	261	Lower-Educated	190	Digital Immigrants	349

Table 7.11: Segments for PLS-MGA

When comparing male and female subjects, two correlational pathways show significant differences, which are both related to personality structures. Particularly, 'Materialism' predicts the affective involvement towards wearable computing much stronger for male consumers than for their female counterparts, as can be seen in Table

7.12. This indicates that materialistic values play a much more important role in the adoption decision process for men than for women.

Moreover, 'Agreeableness' is not a significant predictor for the subgroup 'females', but for the subgroup 'males' it is. Thus, the more a male subject strives for social harmony, the less he is materialistically-oriented. Interestingly, with a β-weight difference of 0.272 this is much less the case in the female subsample. In contrast, for the causal relationship between 'Need for Cognition' and the 'Involvement towards Wearables' significance is narrowly missed at p = 0.056; even though this link is considerably stronger for female persons, the respective H_0-hypothesis, that the path coefficient is not statistically significant, cannot be rejected therefore.

Causal Pathway	β-weight difference	p-Value	Female	Male
Agreeableness -> Need for Materialism	**0,272**	**0,006**	**-0,001**	**-0,272**
Conscientiousness -> Need for Cognition	0,010	0,541	0,057	0,067
Extraversion -> Need for Cognition	0,016	0,441	0,236	0,221
IT Security Risks -> Behavioural Intent to Use Wearables	0,096	0,939	-0,203	-0,107
Involvement towards Wearables -> Behavioural Intent to Use Wearables	0,090	0,820	0,202	0,292
Need for Cognition -> Involvement towards Wearables	0,163	0,056	0,290	0,127
Need for Materialism -> Involvement towards Wearables	**0,143**	**0,957**	**0,197**	**0,340**
Neuroticism -> Need for Materialism	0,044	0,694	0,234	0,278
Openness to Experience -> Need for Cognition	0,041	0,661	0,110	0,151
Perceived Pervasiveness -> Behavioural Intent to Use Wearables	0,041	0,336	0,087	0,046
Perceived Pervasiveness -> Perceived Usefulness	0,056	0,145	0,725	0,669
Perceived Usefulness -> Behavioural Intent to Use Wearables	0,009	0,530	0,458	0,467
Trust -> Behavioural Intent to Use Wearables	0,002	0,492	0,055	0,053
Trust -> IT Security Risks	0,050	0,684	-0,387	-0,337

Table 7.12: Gender group differences

Based on the two 'educational background' subsamples, only one relevant difference occurs due to group effects: The influence of 'Trust in Wearables' on 'Perceived IT security Risk' is comparably strong amongst higher-educated subjects, as illustrated by Table 7.13. This segment-specific impact manifests in a weight difference of 0.160 and is thus sufficiently meaningful. With regard to this finding, it can be concluded that especially in better-educated segments risk perceptions might be attenuated by creating trust towards wearable technologies. Contrarily, the analysis of the present data shows that when dividing the sample based on the educational level, the group-related deviation of the 'Need for Cognition' → 'Involvement towards Wearables' relationship fails slightly to achieve the required significance level of 0.05.

Causal Pathway	β-weight difference	p-Value	Higher edu.	Lower edu.
Agreeableness -> Need for Materialism	0,048	0,335	-0,101	-0,149
Conscientiousness -> Need for Cognition	0,022	0,417	0,091	0,069
Extraversion -> Need for Cognition	0,145	0,902	0,153	0,298
IT Security Risks -> Behavioural Intent to Use Wearables	0,030	0,303	-0,154	-0,184
Involvement towards Wearables -> Behavioural Intent to Use Wearables	0,046	0,326	0,249	0,202
Need for Cognition -> Involvement towards Wearables	0,166	0,948	0,135	0,301
Need for Materialism -> Involvement towards Wearables	0,058	0,248	0,295	0,237
Neuroticism -> Need for Materialism	0,001	0,494	0,279	0,278
Openness to Experience -> Need for Cognition	0,113	0,873	0,081	0,194
Perceived Pervasiveness -> Behavioural Intent to Use Wearables	0,088	0,770	0,019	0,154
Perceived Pervasiveness -> Perceived Usefulness	0,032	0,736	0,690	0,722
Perceived Usefulness -> Behavioural Intent to Use Wearables	0,089	0,221	0,511	0,422
Trust -> Behavioural Intent to Use Wearables	0,050	0,303	0,067	0,034
Trust -> IT Security Risks	**0,160**	**0,950**	**-0,441**	**-0,280**

Table 7.13: Educational level differences

When it comes to age comparisons, no significant group differences become apparent; the found beta weight differences in parameter estimates are shown in Table 7.14. Therefore, in the context of the actual study it is assumed that the structural paths of the Wearable TAM do not substantially differ between the two age groups, since there are no statistically significant deviations in answer patterns observable. However, given that young adults in the age cohort of 18 to 29 are deemed to differ in their technology acceptance patterns and thus represent one specific user group, which should be explicitly considered in technology acceptance research (Hanson, et al., 2011, p. 202; Ha & Stoel, 2009, p. 569), the author decided to perform an additional analysis of age differences. For this purpose, participants were again divided in two segments – participants up to 29 years (N=125) and participants above 29 years (N=349).

Causal Pathway	β-weight difference	p-Value	Old	Young
Agreeableness -> Need for Materialism	0,022	0,583	-0,094	-0,116
Conscientiousness -> Need for Cognition	0,015	0,564	0,074	0,058
Extraversion -> Need for Cognition	0,086	0,806	0,249	0,163
IT Security Risks -> Behavioural Intent to Use Wearables	0,003	0,528	-0,167	-0,170

Causal Pathway	β-weight difference	p-Value	Old	Young
Involvement towards Wearables -> Behavioural Intent to Use Wearables	0,056	0,724	0,275	0,218
Need for Cognition -> Involvement towards Wearables	0,017	0,430	0,215	0,232
Need for Materialism -> Involvement towards Wearables	0,079	0,791	0,283	0,205
Neuroticism -> Need for Materialism	0,097	0,863	0,293	0,196
Openness to Experience -> Need for Cognition	0,011	0,543	0,130	0,120
Perceived Pervasiveness -> Behavioural Intent to Use Wearables	0,131	0,079	0,017	0,148
Perceived Pervasiveness -> Perceived Usefulness	0,065	0,076	0,682	0,747
Perceived Usefulness -> Behavioural Intent to Use Wearables	0,000	0,499	0,444	0,444
Trust -> Behavioural Intent to Use Wearables	0,042	0,673	0,076	0,034
Trust -> IT Security Risks	0,064	0,745	-0,335	-0,399

Table 7.14: Age differences

The comparative analysis shows three significant differences between young adults and older age categories, which are summarised in Table 7.15. Surprisingly, the first major insight is that IT security concerns act as a significantly stronger inhibitor of technology adoption behaviour among subjects in their early adulthood than compared to their older counterparts. This insight is particularly remarkable since one would expect that young people are more willing to take risks in general and information security risks in particular. Here, it might be argued with the concept of 'generational cohorts', which is regarded to be more useful in analysing markets than static age segmentations (Schewe, et al., 2000, p. 108 f.). Unlike a generation, which is defined as spanning 20-25 years, a cohort is primarily constituted by external events which lead to changes in the behaviour or values of people.

This research consequently focusses on the comparison of two generational cohorts: the generational cohort of 'digital natives' (sometimes also referred to as 'Generation Y' or 'Net Gen') and 'Digital Immigrants'. According to Vodanovich et al. (2010, p. 711 f.), digital natives are those who "[…] were grown up immersed in a networked world, with access to ubiquitous digital technologies and the ability to learn and use them in fluent and sophisticated ways". Based on this segmentation, the outcome of the present PLS-MGA analysis goes in line with the current research. The results indicate that 'Generation Y' perceives privacy risks even more than 'Generation X' does and that, generally, both cohorts are significantly influenced by information security concerns (Lösing, 2016, p. 10). This might result from the digital natives' greater awareness of the Internet. Members of this generation are actively participating in the new digital media culture and do have accounts in multiple social media networks, where privacy risks may be even more present.

Causal Pathway	β-weight difference	p-Value	Immi.	Natives
Agreeableness -> Need for Materialism	0,016	0,572	-0,110	-0,126
Conscientiousness -> Need for Cognition	0,056	0,661	0,075	0,019
Extraversion -> Need for Cognition	0,058	0,284	0,206	0,264
IT Security Risks -> Behavioural Intent to Use Wearables	**0,149**	**0,984**	**-0,135**	**-0,284**
Involvement towards Wearables -> Behavioural Intent to Use Wearables	0,071	0,790	0,275	0,204
Need for Cognition -> Involvement towards Wearables	0,131	0,874	0,253	0,121
Need for Materialism -> Involvement towards Wearables	0,056	0,676	0,268	0,212
Neuroticism -> Need for Materialism	0,070	0,605	0,284	0,214
Openness to Experience -> Need for Cognition	**0,265**	**0,985**	**0,188**	**-0,077**
Perceived Pervasiveness -> Behavioural Intent to Use Wearables	0,075	0,220	0,036	0,111
Perceived Pervasiveness -> Perceived Usefulness	0,019	0,600	0,707	0,688
Perceived Usefulness -> Behavioural Intent to Use Wearables	0,041	0,370	0,450	0,491
Trust -> Behavioural Intent to Use Wearables	0,111	0,870	0,073	-0,038
Trust -> IT Security Risks	**0,213**	**0,987**	**-0,315**	**-0,528**

Table 7.15: Generational cohort differences

Moreover, as compared with the older generational cohort, study participants born between 1986 and 1996 demonstrated a significantly lower level of perceived information security risk when they reported a trusting stance towards wearable technologies. This result is consistent with the findings of prior studies, which indicate that digital immigrants are less driven by underlying affective factors and that they more hesitantly adopt new technologies, as they frequently don't consider themselves as reasonably technology-savvy and as being in control of security risks (Morris & Venkatesh, 2009, p. 392; Miltgen & Peyrat-Guillard, 2014, p. 107 f.). Accordingly, higher levels of 'computer self-efficacy' defined as the self-assessment of one's computer competence – which is particularly inherent to digital natives – may moderate attitudinal relationships in an ICT adoption context (Topolovcan & Matijevic, 2015, p. 163; Marakas, et al., 1998, p. 126). Additionally, in terms of generational cohort differences, the multigroup comparison shows that the relationship between 'Openness to Experience' and 'Need for Cognition' is significant only for the older section of the subdivided sample. Thus, it can be concluded that individuals born before 1996 are more likely to engage in effortful thinking when they are broad-minded and intellectually curious as compared to their younger counterparts. In contrast, this causal nexus does not hold to the same extent for digital natives. This could be explained by the fact that the 'Net Gens' are generally characterised by their preference for social openness, multitasking, and learning through discovery, which has a direct bearing on how they learn (Ryberg, et al., 2010, p. 303; Kivunja, 2014, p. 102).

In conclusion, the PLS-MGA analysis revealed several important insights, which can be directly used for deriving concrete praxeological recommendations. Nevertheless, it should be noted that only very few differences exist between demographic segments when it comes to wearable computing adoption. While gender differences refer primarily to personality-related correlates of behaviour, the 'digital divide' of the sample population results in substantially diverging IT security perceptions and risk processing relations, which require a more differential perspective on the structural model. At the same time, no significant age differences could be proven empirically, whereas a single, trust-related deviation in response patterns can be observed when comparing individuals with different educational backgrounds.

7.3.4 Analysis of Total Effects and Performance of Constructs

In order to holistically examine the role of a particular target construct's key sources, the total effects of the path model (importance) and the average values of the latent variable scores (performance) need to be assessed (Ringle & Sarstedt, 2016, p. 1867). The **importance-performance map analysis** (IPMA) contrasts the total effects (i.e. the sum of direct and indirect effects) of antecedent constructs with the average values of their latent variable scores and, thereby, extends the standard PLS reporting in order to "present in an easily understandable and convincing manner the results of success factor research" (Henseler, 2016, p. 1843). By implication, this method can highlight significant areas for improvement of management activities and thus help decision makers to prioritize their actions. Consequently, performance improvement of a construct that exhibits a low average score but at the same time a strong influence on the target construct would be an effective anchor point.

The PLS-IPMA performance values are determined by indicator scores, which are rescaled on a range between zero (lowest performance) and 100 (highest performance) to facilitate interpretation of performance levels. According to Ringle and Sarstedt (2016, p. 1868), applications of IPMA must meet three requirements. Firstly, all indicators in the structural model must use a metric or quasi-metric scale. Secondly, none of the indicators should be reverse coded, so all variables are in the same direction. Otherwise it could not be concluded that a higher construct score represents a better performance. Thirdly, irrespective of formatively or reflectively measured constructs, all outer weight estimates must be positive.

As this study epistemically focusses on the adoption of wearable computing, all direct effects on the endogenous target variable should be considered. In view of the perceived risk facets, this would also involve reverse coded items. The indicator coding of the first-order constructs of *Perceived IT Security Risk* has therefore been rescaled, so the requirements for IPMA application were met and for all of the indicators a higher value represents a better outcome. The focal reverse-scaled higher-order construct may be reinterpreted in terms of the *perceived security* of wearable technologies. Moreover, as both composite indicators *NZ04_03* and *LOC_Availability* yield negative outer weights, these indicators were removed to meet the above requirements – especially, since the analysis should be conducted solely on the construct level. The summary of the obtained IPMA data is presented in Figure 7.5.

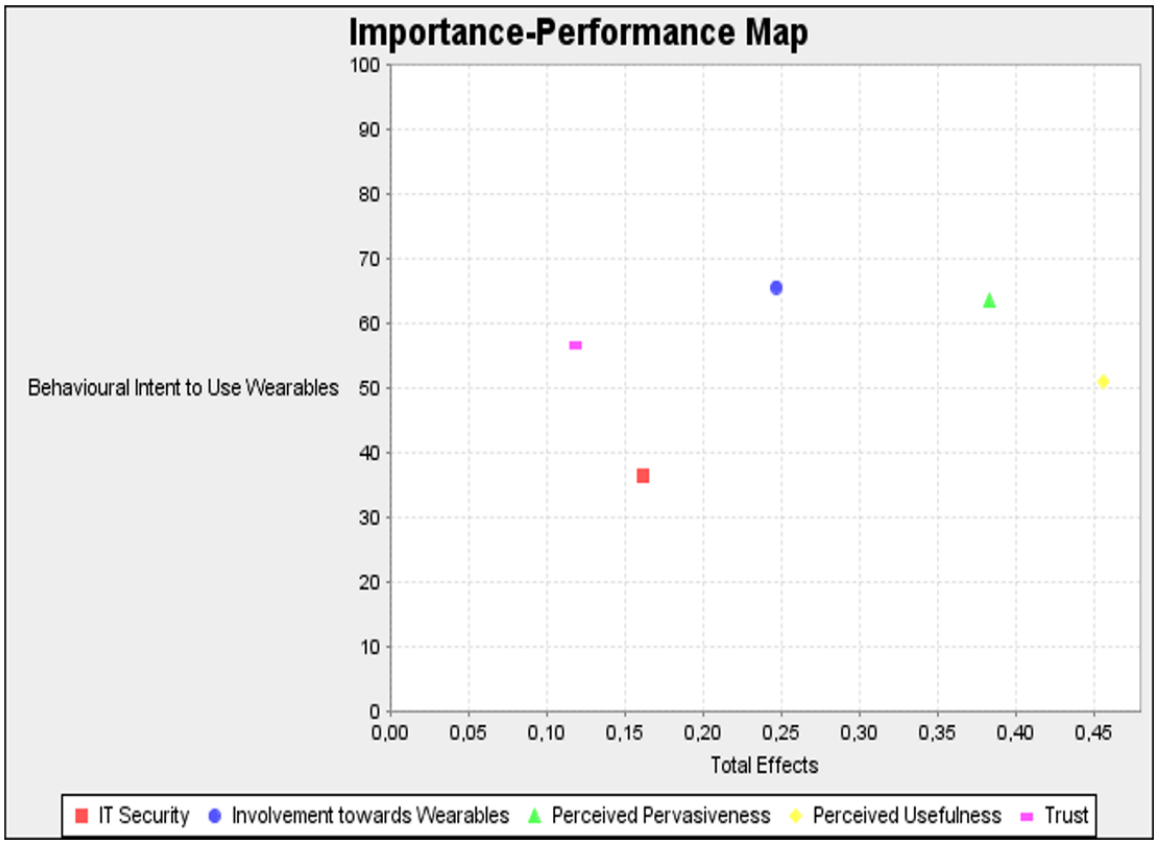

Figure 7.5: Total effects and performances of antecedent constructs of the intention to use wearables

In the created importance-performance map, the x-axis depicts the total effects of the direct predictors of the target phenomenon *Behavioural Intention to Use Wearables*. The y-axis represents the average rescaled latent variable scores (i.e. the performance) of the five determinants. As can be seen from the results of the combined assessment of total effects and performances, the construct *Perceived Usefulness*, located at the lower right area of the importance-performance map, possesses the lowest performance-importance ratio. Thus, there is a particularly high potential for improving the performance of this decision parameter. When looking at the total effects, improvement of aspects related to the *Perceived Pervasiveness* of wearables follows as a second priority. Given the poor performance value of *Perceived IT Security* (≈36.54), improving consumer attitudes towards the information security of wearable technologies should also come more to the fore. Contrarily, boosting the performance of trusting beliefs towards wearables would has the lowest relevance for managerial actions due to this perspective.

7.3.5 Summary of Findings

Having determined the reliability and validity of the outer and inner structures of the evolved Wearable TAM, in the following the formulated hypotheses are conclusively accepted or falsified where appropriate in order to prepare the ground to answer the praxeological research question.

The proposed causal relationships have been quantitatively tested with the help of a representative sample of 474 potential German adopters of wearable computing, which is assumingly not subject to any bias such as common

method bias. With regard to representativity, the comparison of the drawn sample with the target group of potential adopters of wearable computing in Germany shows a good match. Furthermore, the questionnaire items of the web-based survey developed for each psychological construct were based on both qualitative study results and a comprehensive literature review of pertinent empirical research. Particular attention was devoted to the questionnaire design including the cover letter and the question sequence, which certainly contributed to the high questionnaire completion rate. Moreover, the empirically assessed measurement instruments work well in terms of reliability and validity on the item and on the construct level and only minor adjustments were necessary in order to meet the pertaining quality criteria. Taken together, the results of the multivariate assessment of the structural theory and its concepts indicate that the conducted quantitative study fits all the basic requirements of empirical research. The obtained findings are thus suitable for empiricist verifying the hypotheses proposed in this thesis.

For judging the direct effects, magnitude and significance of regression coefficients were consulted. Indirect effects were assessed by relying on two regression coefficients: A mediational hypothesis is deemed supported if both path coefficients of the indirect pathway are in the hypothesized direction and significant. It is partially supported, if the direct path coefficient meets these two criteria, too. Likewise, for evaluating moderating effects a hypothesis is supported if the beta estimate of the interaction term is significant and in the proposed direction, yielding a sufficiently large effect size (i.e. $f^2 \geq .005$). The theoretical propositions were tested on the .05 level. Table 7.16 summarises the hypotheses as well as their structural parameters, effect sizes, and the corresponding overall evaluation. For mediational hypotheses, path coefficients pertaining to the indirect effects are shown, whereas for moderator hypotheses coefficients of the interaction terms are displayed.

ID	Hypothesis	β ≥0.1	Sig. ≥0.05	f^2 ≥0.005	Overall Evaluation
H_1	Increased consumer's perception of the usefulness of wearable computing will result in an increase in the intention to use a wearable computing device.	0.456	***	0.326	Confirmed
H_2	Increased consumer's perception of the security risk of wearable computing will result in a decrease in the intention to use a wearable computing device.	-0.161	***	0.083	Confirmed
H_3	Increased consumer's perception of trust in wearable computing devices and services will result in an increase in the intention to use a wearable computing device.	0.060	n.s.	0.003	Not confirmed
H_{3a}	The relationship between the level of trust towards wearable computing devices and services and the intention to use wearables is mediated by perceived security risk.	0.058	***	0.148	Confirmed
H_4	Increased consumer's perception of the pervasiveness of wearable computing devices will result in an increase in the intention to use a wearable computing device.	0.064	n.s.	0.004	Not confirmed

ID	Hypothesis	β ≥0.1	Sig. ≥0.05	f^2 ≥0.005	Overall Evaluation
H_{4a}	The relationship between the level of consumer's perception of the pervasiveness of wearable computing and the intention to use wearables is mediated by perceived usefulness.	0.318	***	0.951	Confirmed
H_5	Increased consumer's level of neuroticism will result in an increase in consumer materialism.	0.258	***	0.071	Confirmed
H_6	Increased consumer's level of agreeableness will result in a decrease in consumer materialism.	-0.113	**	0.014	Confirmed
H_7	Increased consumer's level of openness to experience will result in an increase in the need for cognition.	0.128	**	0.016	Confirmed
H_8	Increased consumer's level of extraversion will result in an increase in the need for cognition.	0.214	***	0.041	Confirmed
H_9	Increased consumer's level of conscientiousness will result in an increase in the need for cognition.	0.057	n.s.	0.003	Not confirmed
H_{10}	Increased consumer's level of materialism will result in an increase in affective involvement.	0.251	***	0.071	Confirmed
H_{11}	Increased consumer's need for cognition will result in an increase in affective involvement.	0.220	***	0.055	Confirmed
H_{12}	Increased consumer's affective involvement will result in an increase in the intention to use a wearable computing device.	0.247	***	0.101	Confirmed
H_{M1}	The relationship between the perceived usefulness of wearable computing and the behavioural intention to adopt is positively moderated by the product category-related innovativeness.	0.066	***	0.018	Confirmed
H_{M2}	The relationship between the perceived security risk of wearable computing and the behavioural intention to adopt is negatively moderated by the product category-related innovativeness.	-0.035	n.s.	0.005	Not confirmed
H_{M3}	The relationship between the perceived usefulness of wearable computing and the behavioural intention to adopt is positively moderated by the level of personal experience.	0.076	***	0.021	Confirmed
H_{M4}	The relationship between the perception of the security risk of wearable computing and the behavioural intention to adopt is negatively moderated by the level of personal experience.	-0.019	***	0.001	Not confirmed
Notes: significance level *p≤0.1; **p≤0.05; ***p≤0.01 (two-sided)					

Table 7.16: Results of hypothesis testing

The empirical findings confirm most of the formulated hypotheses (13 out of 18). All of the calculated path coefficients are in the proposed direction. Regarding the moderator hypotheses H_{M2} and H_{M4}, the obtained significance value and effect size, respectively, does not suffice to establish a meaningful impact. The remaining three rejected hypotheses (H_3, H_4 and H_9) are dismissed due to lack of statistical significance. In terms of proposed

indirect effects, both mediational hypotheses H_{3a} and H_{4a} receive empirical corroboration. Yet, the former hypothesis is only partially supported due to a small total effect of the mediated relationship.

In order to deepen the understanding of the relevant research context, after all hypotheses were tested a multigroup analysis was conducted to provide additional information. Similar to moderator hypothesis testing, assumptions about group differences are supported if most regression estimates are significantly different when subsamples are compared. Since just a fraction of the beta weight discrepancies is significantly different from zero for the given pairs of models (cf. section 7.3.3), the supposed group-specific heterogeneity in data receives only partial support. To conclude, the PLS multigroup comparison for demographic control variables does not severely question the results of the main effects model. Therefore, the obtained parameter estimates are considered robust with respect to group effects. Overall, the generated findings are indicative of the main effects model's capability to predict the target construct of wearable computing adoption.

7.4 Interpretation of Results

Along the lines of the research questions outlined in chapter 1.2, in this chapter the study's empirical key findings from the previous sections are critically discussed. To form a holistic picture, the results are confronted with the germane body of literature. In particular, the discussion focusses on the role of the predictors in the synthesised structural model as well as on the interacting effect of several salient segmentation variables. Based on these considerations, concrete recommendations for marketing researchers and practitioners are derived in chapter 8 in order to effectively address the opportunities and challenges in wearable technology markets.

The main research objective of this study was to theoretically and empirically investigate the success factors of the adoption of wearable computing. Guided by the concepts which successively evolved during the qualitative study and literature review, a new causal model that interconnects the identified acceptance factors, the Wearable TAM, could be developed and subsequently tested. The underlying assumption of this model is that the intention to use wearables in the sense of a conative attitudinal component has a two-fold nature: It is determined by both cognitive beliefs (denoted by hypotheses H_1 and H_2) and the product category-related involvement, which intrinsically relates to the affective dimension of attitude (H_{12}). At the upstream level of explanation, perceived pervasiveness (H_4) and trust (H_3) in wearable technologies are hypothesised to shape the individual acceptance judgment indirectly in terms of exogenous latent variables. Moreover, as per directional hypotheses H_5 to H_9 the theoretical framework proposes a fully mediated, hierarchical model of dispositional predictors of adoption behaviour. Figure 7.6 gives an overview of the predictor structure formulated in this thesis. Non-significant relationships are not illustrated for the sake of conciseness.

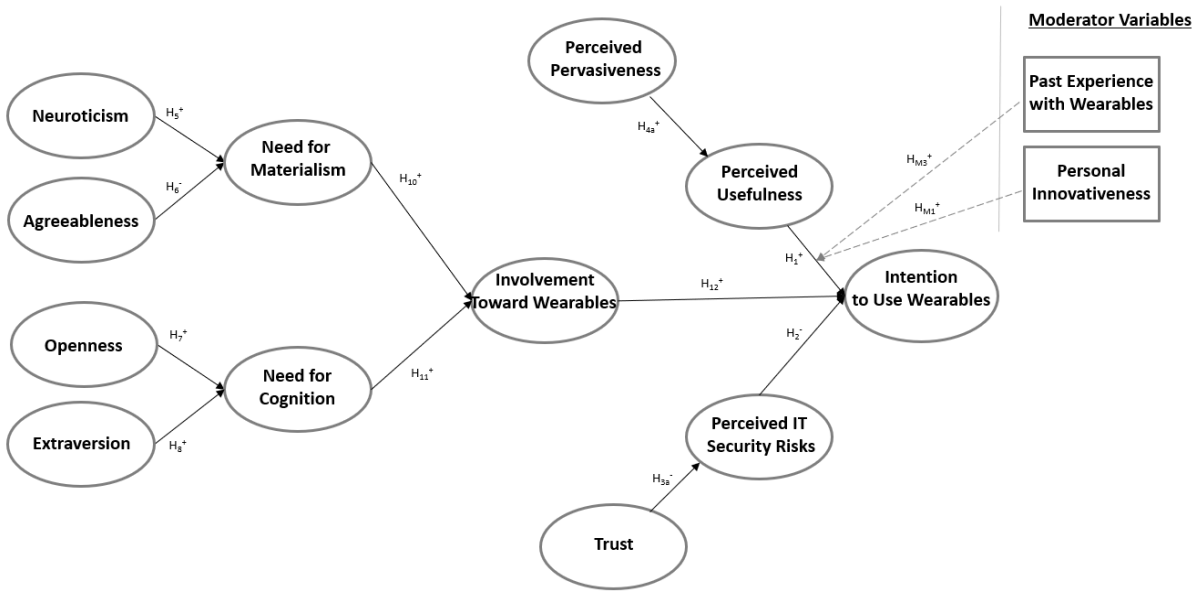

Figure 7.6: Final conceptual model on wearable computing acceptance

The obtained structural parameters together with further relevant quality criteria (which are basically derivable from regression weights and significance levels) substantially enrich the extant body of knowledge regarding the interplay of inter-individual factors that motivate IT usage intentions. More precisely, the conducted path analytical examination – under particular consideration of group effects and the constructs' individual performances and total effects – provide valuable insights into the nomological network of technology acceptance constructs. In addition to traditional reflective arrays of indicators, the postulated framework integrates three formatively operationalised latent variables, where two of these formative constructs are of a hierarchical nature. As a result, in the following sections special attention is also devoted to formative structures in terms of success driver analyses. Finally, follow-up considerations of relevant control variables allow to further clarify the dependency patterns of the developed path model as a way to deepen understanding of consumer behaviour in innovative technology markets.

Consistent with the apriorically formulated system of hypotheses, parameter estimates provide evidence to support the attitude-forming effect of eleven out of twelve hypothesised constructs. Consequently, out of 14 causal claims only three hypotheses could be falsified empirically for the given data. Furthermore, a great portion of variance in the dependent cognitive variables is accounted for by the conceptualised exogenous constructs as implied by the multiple determination coefficients. This may be regarded as indicative of the overall goodness-of-fit of the model. As expected, the quantitative study proves that *Perceived Usefulness* represents the strongest predictor of *Behavioural Intention to Use Wearables*. With a beta value of 0.456 this factor significantly contributes to the portion of explained variance in the target phenomenon of interest, whose total response variation is jointly explained with more than 67% by its regressor variables. This finding demonstrates even further the robustness of the TAM in a wearable computing setting. In a broader research context, *Perceived Usefulness* was consistently found to be a major source for technology acceptance (Planing, 2014 p. 250). Accordingly, judgement formation is dominated by cognitive decision rules, rather than by affective attitudinal responses. Even though the hypothesised relationship H_{12} describing the influence of affect-laden involvement on usage intention shows a high level of relevance and validity ($\beta = 0.247$, $p < 0.01$), it provides a comparably small explanatory contribution. The population parameter estimates are in concert with findings from the qualitative stage of research and prior

acceptance studies, which suggest focussing more on cognitive beliefs instead of affective determinants in explaining and predicting information technology use (Yang & Yoo, 2004, p. 26). It may be argued that the usage of a specific information system often represents a means-end behaviour, which emphasises the instrumental nature of technology adoption decisions (Bhattacherjee, 2001, p. 375). Remarkably, the computed R-squared value of 0.677 for *Intention to Use* points out the predictive capacity of the model.

The formative operationalisation of the *Perceived Usefulness* construct makes it possible to gain additional insights into the importance of acceptance drivers. In regard to the relative impact of its manifest measures, for German adopters the perceived support of health and fitness constitutes the major motive for utilising wearables. This is certainly largely due to the fact that in 2016 – at the time of the undertaken online survey – wearable computers were predominantly used for fitness purposes by end consumers (Graziano & Stein, 2016). Hence, many survey participants may have located wearable computers primarily in the field of sports analytics and fitness. In that respect, it is worth noticing that wearable health and fitness devices such as activity trackers represent highly specialised information systems in the pertaining sports and medical device markets (FHI, 2016). Accordingly, the finding underscores the substantial relationship between perceived functional utility and positive valuation of ICT innovations. As implied by the exploratory study, the second-strongest predictor of usefulness perceptions and thus, indirectly, of usage intention is the expected enhancement of personal abilities. Once again, the analytical results hereby implicate that instrumentality considerations may override affective motives in stimulating adoption decisions. With smaller outer weights but still significant at a .05 level, beliefs that wearables could help to feel more in control of life and enhance social relationships, respectively, are less important for index formation. On basis of the lacking statistical significance, the perceived technology-enabled boost of one's self-confidence renders not relevant for explaining cognitive responses. Again, this emphasises the utilitarian reason for ICT acceptance and provides further support for a more pragmatic understanding of wearables. Taken together, the findings suggest that extrinsic motives and instrumental behaviours are indeed prevalent in information technology usage.

Correspondingly, when inspecting the importance-performance matrix, it becomes apparent that in a ceteris paribus situation *Perceived Usefulness* is of highest importance for shaping the conative attitude but, simultaneously, shows a fairly low performance with an average latent variable score of 4.082. Managerial action should therefore be primarily directed at increasing benefit perceptions. Given its total effect amounting to 0.319, *Perceived Pervasiveness* turns out to have somewhat less priority for performance betterment. Notably, whereas pervasiveness dimensions (i.e. ubiquity, context-awareness, and unobtrusiveness) mainly address hardware issues such as sensing capabilities and form factor, tangible benefits ultimately arise from software applications. Through proper user interfaces and interaction concepts, 'apps' provide users with access to the relevant electronics and information services (NGRAIN, 2016). The empirical importance of consumer usefulness perceptions hence connotes the crucial role software platforms and applications play in generating more compelling value propositions.

In line with the conceptual framework formulated in this study, the analysis of mediating effects empirically underpins the theoretic assertion that the influence of *Perceived Pervasiveness* on behavioural intention is completely mediated by individual usefulness perceptions. For this reason, the direct causal hypothesis H_4 has to

be rejected. This means that the unique technological features that distinguish pervasive computing from the classical desktop paradigm only take effect on device usage if they are translated into concrete applications that are found to be useful. This result fits earlier conceptual and empirical works, which indicate that motivational variables entirely mediate system design features, which in turn have no additional direct effect on system use (Davis, 1993 p. 482). With a path coefficient of 0.698 and an error probability below 0.01, consumer perception of the particular characteristics of pervasive information systems highly significantly predicts individual benefit expectations. Likewise, the effect size of *Perceived Pervasiveness* can be considered extremely large ($f^2 = 0.951$). Against the backdrop of the large R^2-value of *Perceived Usefulness*, it is reasonable to assume that cognitive beliefs regarding a wearables' positive utility are substantively formed by perceptions of system pervasiveness. In fact, this is in line with the general argumentation of Karaiskos (2009) who found that pervasiveness dimensions represent mediated drivers of acceptance. However, a more accurate picture is obtained by looking at the average score of individual components of the perceived pervasiveness construct. An overview of all mean values of first-order latent variable scores obtained from descriptive analysis is given in Table 7.17. Here it becomes apparent, that survey respondents averagely tend to perceive *Unobtrusiveness* to be the least developed pervasiveness dimension. As a consequence, particular attention should be paid to the design of input modalities and form factor to improve social acceptability. Considering the pseudo t-values obtained from re-sampling, nonetheless, all drivers of *Perceived Pervasiveness* can be regarded highly significant on a 0.01 level. Whilst perceived ubiquity has the largest effect on its composite construct, unobtrusiveness perceptions and, lastly, context-awareness expectations both contribute to conative attitude variability with almost even predictive efficiency (0.369 and 0.335, respectively).

Construct	**Mean Score**	**Standard Deviation**
Intention to Use	4.050	1.885
Perceived Usefulness	4.082	1.623
Perceived Pervasiveness	4.810	1.196
Perceived IT Security Risk	4.477	1.894
Trust	4.391	1.355
Involvement	4.912	1.552
Materialism	3.743	1.337
Need for Cognition	4.040	1.262
Neuroticism	3.336	1.271
Agreeableness	4.180	1.296
Conscientiousness	5.331	1.102
Openness to Experience	5.136	1.199
Extraversion	4.532	1.332
Ubiquity	5.074	1.526

Construct	Mean Score	Standard Deviation
Context-Awareness	5.031	1.283
Unobtrusiveness	4.241	1.398

Table 7.17: Non-standardised mean scores of Wearable TAM latent variables

It is not only the obtained survey statistics, but also insights gained from the exploratory study which reveal that behavioural models on wearable computing usage intention should employ a 'net valence' perspective of attitude, which takes both subjective positive (benefit expectations) and negative valences (risk perceptions) of adoption behaviour into account. More precisely, *Perceived IT Security Risk* proves to be a statistically significant usage inhibitor. Albeit this hierarchical construct has a fairly small direct effect on usage intention as compared to pervasiveness perceptions, when embedding it into the structural model the resulting PLS inner estimates are clearly indicative of nomological validity (β = -0.161). In other words, the performance value of *Behavioural Intention to Use Wearables* decreases as security risk perceptions intensify. This result conforms to the directional hypothesis H_2, which postulates a negative relationship between anticipated risks and favourable attitudes towards the judgemental object. The risk concept thereby counteracts the pro-innovation bias inherent to most innovation diffusion studies. Importantly, since PLS-SEM intrinsically tends to underestimate the correlations between second-order constructs and other latent model variables, the comparably low path coefficient of the risk-intention link should be considered with appropriate caution. Yet, another interesting aspect becomes apparent when taking a closer look at group-specific effects: Even though the causal risk-attitude link renders highly significant in all subsamples, the resulting beta changes for generational cohorts (i.e. digital natives and digital immigrants) are quite meaningful with a probability of error below 1%.

The findings in regard to the inner components of the structural model can be extended by interpretation of outer weights of the single risk dimensions integrated into the formative measurement scale. Estimation results of PLS driver analysis suggest that information confidentiality is a major cause for consumer resistance towards wearable computing. At the same time, descriptive statistics regarding the inverted construct values illustrate a relatively low performance (i.e. low average latent variable score) of privacy protection. Table 7.18 shows the unstandardized mean values of the risk dimensions having reverse scored items. This statistical outcome backs current research, emphasising privacy concerns that are posed by the increased means of continuously collecting, storing, and processing personal data (Motti & Caine, 2015, p. 231). When it comes to wearable computing security, issues of data confidentiality should thus receive first priority from a consumer point of view. Also, integrity of data renders significant in the decision to adopt respective socio-technological systems. In contrast, the availability facet even shows a negative weight sign due to suppressor effects. However, in terms of absolute importance, exclusion of this explanatory variable would restrain the conceptual meaning of its assigned higher-order construct. Therefore, this indicant should be retained in the model.

Risk Dimension	Mean Score	Standard Deviation
Confidentiality*	2.935	1.792
Availability*	3.850	1.464
Integrity*	3.755	1.541
Notes: *reverse scored items		

Table 7.18: Non-standardised mean scores of first-order risk dimensions

In terms of indirect effects, the survey data reveal that *Perceived IT Security Risk* partially mediates the impact of *Trust in Wearables* on the target phenomenon (VAF = .492). Hence, the level of perceived technology risk depends, at least partly, on the extent to which a prospective adopter beliefs in the trustworthiness of the respective system. To put it another way, trust in wearable computing reduces behavioural uncertainty and related subjective risks associated with the technology's functionality and predictability. In support of this, Pavlou (2003, p. 93) found empirically that the directionality of the causal association between both socio-psychological constructs flows from trust to perceived risk. He inferred therefrom, that trust may act indirectly on intention formation through the mediating effect of perceived risk. Consequently, the present study findings may be regarded as a response to his call for further research on the complex interrelationship among trusting beliefs and risk perceptions, seeking to integrate the still fragmented theories on the risk concept in Information Systems research. From current confirmatory analysis it can thus be concluded, that the postulated relationship between trust and intention (denoted by hypothesis H_3) has to be discarded. Rather, it can be assumed that there are further third variables which may act as mediators of trustworthiness. Moreover, understanding of the trust-risk nexus can be deepened by means of PLS multigroup analysis, which clearly shows that both educational level and generational cohort moderate the effect of trust on perceived security risk. The inclusion of both control variables leads to a substantial increase in R^2-values (i.e. an increase of 0.115 for educational and 0.18 for generational cohorts). From this it can be concluded that trust plays a more vital role in encouraging better-educated population segments as well as 'Net Gens' to use wearables.

Based on evidence from both exploratory study and confirmatory regression analysis, intrinsic involvement qualifies as another essential source of technology adoption behaviour under a wearable computing scenario. Analytic results indicate a direct positive and significant relationship between personal relevance of an information system and the intention to use it ($\beta = 0.247$), which is why hypothesis H_{12} cannot be disconfirmed. Due to high cross-loadings on conative attitude (i.e. usage intention) as indicated by the items *IV01*_03, AZ03_*02* and *AZ03_03*, product-related involvement was found to reflect an affective component of attitude. This observation conforms to previous attitude research, which has linked behavioural involvement to an affective state of mind (Palmer, et al., 2013, p. 145). The finding hereby lends new validity to the theoretical assumptions of the tripartite model of attitude structure and, moreover, highlights the great importance of the focal concept in predicting and explaining volitional human actions within a technology adoption context. Though the achieved R-squared value in the amount of 0.112 appears relatively poor, owing to its statistical significance the OLS regression on involvement can be considered a good estimator in social sciences and personality psychology, given the inherent irregularities and uncertainties in human behaviour (Wooldridge, 2015, p. 35; Nozick, 2001, p. 294; Cziko, 1989,

p. 17). In spite of the seemingly noisy, high-variability residuals, the predecessor constructs of involvement still provide valuable information about tendencies in consumer responses – particularly, as this thesis does not aim at precisely predicting intrapsychic predispositions, but rather at determining which explanatory traits are statistically significant and how one-unit increases in these individual difference variables relate to changes in the emotional attitude towards wearables. Hence, for the sake of model parsimony, no further explanatory variables and pathways were added to the Wearable TAM to artificially increase its predictive value.

Adopting the reasoning of Mowen (2000), the present study conceptualises involvement as a consumption-relevant situational trait that entirely mediates underlying dispositions in terms of a hierarchical personality structure. In line with literature, empirical data indicates that *Need for Material Resources* and *Need for Cognition* jointly evoke personal commitment towards innovative information systems at lower level of abstractness, which is why both hypotheses H_{10} and H_{11} can be confirmed. As compared to need for cognition, the former compound personality characteristic is more predictive of situational traits ($\beta = 0.251$, $p < 0.01$). This hypothetico-deductive finding clearly underlines the materialistic dimension of the early adopter of wearable computing. A closer examination of results shows that this positive relationship holds even more true in the male subsample, yielding a structural coefficient of 0.340 and a t-value far above the critical threshold of 2.57. Accordingly, earlier studies on gender differences in consumer behaviour suggest that men score generally higher in terms of materialism and consumption patterns (Segal & Podoshen, 2013, p. 190). Yet, in view of the fairly small structural parameters achieved, it has to be acknowledged that although significant, the correlations between materialism and personality characteristics were typically weak across preceding empirical studies, ranging from −0.37 to 0.33 (Górnik-Durose & Pilch, 2016, p. 103). In a similar vein, need for cognition is significantly related to attitudinal outcomes ($\beta = 0.220$, $p < 0.01$), whereas the path coefficient is considerably higher in the female subsample ($\beta = 0.290$) than compared to the male group ($\beta = 0.127$). However, the produced beta change barely misses the 5% level of significance. Thus, there is no satisfactory evidence to suggest that male adults are less affected by cognitive motivation than their female counterparts in regard to wearable computing enthusiasm. In respect of predictive competency, validation of the inner model confirms that both, materialistic values ($R^2 = 0.088$) and need for cognition ($R^2 = 0.091$) represent highly complex, multi-causally determined traits, which may not be sufficiently explained by the Big Five personality dimensions.

At most elemental level of personality structure, neuroticism and agreeableness are both found to significantly interact with materialistic values. As a consequence, the directional hypotheses H_5 and H_6 on the causes of materialism are respectively corroborated. Showing a path coefficient of 0.258 and an error probability < .01, neuroticism has the strongest formative influence on the outcome variable. In contrast, the tendency to be pleasant and accommodating in social situations is significantly negatively correlated with materialism ($\beta = -0.113$). It may be concluded therefrom, that high neuroticism and low agreeability jointly reflect an important predispositional source of materialistic tendencies, what strongly conforms to previous research in the field of personality psychology (Watson, 2014, p. 197). However, follow-up analysis of group differences revealed that gender-related patterns substantially shape the distribution of responses: The negative relationship between agreeableness and materialism is only significant for male subjects, producing a beta coefficient of -0.272 in the pertaining submodel. Thus, the inhibitory effect of agreeableness on materialistic attitudes may solely be expected among the male population segment. This result corresponds with the broad body of research on gender differences in personality,

which posits that the connection strength between agreeableness and other motivational traits strongly varies with gender (Rey & Extremera, 2016, p. 105; Chapman, et al., 2007, p. 1594).

Furthermore, the findings on need for cognition suggest that extraversion is a significant personality antecedent, which positively affects individual differences in cognitive activity on a .01 level ($\beta = 0.214$). Having a beta value of 0.128 and a two-sided p-value below .01, openness to experience emerges as the second most influential determinant of consumer responses as regards the inclination to cognition. In-depth analyses via group comparison, however, show that salience of this trait varies with generational cohort. From PLS-MGA it follows that digital immigrants – characterised by a beta increase of 0.265 – were more likely to engage in effortful thinking when they scored high in intellectual curiosity as compared to digital natives. By challenging prior research in the field, this new insight surely warrants further scientific studies about the moderating effect of generational cohorts on personality correlates. In view of their satisfactorily low error probability ($p < .01$ for two-sided tests) at aggregate model level, both theoretical assertions H_7 and H_8 are accepted.

On the contrary, due to non-significance of parameter estimates, questionnaire data does not provide any evidence in favour of a positive association between conscientiousness and the motivation for cognitive challenges, why hypothesis H_9 can be regarded as being falsified. Here, it may be argued that related research on personality traits frequently reported contradictory results on conscientiousness-personality relations (Soubelet & Salthouse, 2011, p. 304). For instance, published correlations between cognitive capacity and conscientiousness have sometimes been negative and sometimes either positive or zero. Literature provides some indication for this mixed evidence. According to the Intelligence Compensation Hypothesis (ICH) some "[…] individuals with low cognitive ability become more organized, hardworking, and persistent over time as a means of compensating for their low ability […]" (Curtis, et al., 2015, p. 14; Moutafi, et al., 2004, p. 1013). In challenging this line of reasoning, Murray et al. (2014, p. 21) point out that cognitive functioning and conscientiousness-related traits mutually influence one another and that the impact is heterogeneous across individuals but nearly zero in the aggregate. For instance, persons with low ability may become discouraged by their failures and could grow to expend less effort acting conscientiously and vice versa. The scholars infer from their study results that selected research samples comprised of participants with occupational or academic achievement above certain thresholds would artificially bias the association in the negative direction. Assuming a positive link between need for cognition and cognitive ability (Hill, et al., 2016, p. 225), and considering the current sample structure, which is clearly skewed towards better-educated participants, a similar effect may be expected for the produced parameter estimates. The impact of conscientiousness might be cancelled out by effects in the opposite direction. Therefore, future research should account for further interacting variables such as achievement-striving or social setting, which probably confound the ramifications of conscientiousness. Nevertheless, except this single suspicious correlation, in total the present study supports the general applicability of the 3M model of motivation to explain consumer behaviour in innovative technology markets.

To elaborate context-relevant insights that go beyond the postulated model structure, additional in-depth analyses were performed on the attitudinal relationships of the Wearable TAM. Specifically, the contingencies of the strength of the relationships between the attitude-linked cognitive variables were modelled by means of the a priori identified background variables *Personal Innovativeness* and *Past Experience*. In a technology acceptance context,

both adopter-specific characteristics appear to be particularly informative exogenous factors (Rogers, 2010 p. 268; Gefen, et al., 2003b p. 307; Venkatesh, et al., 2003 p. 442). The moderation analysis revealed that the level of innovativeness and past experience with wearables both provide a significant explanatory contribution to the base model. This means that raters, who are latently innovative or relatively familiar with wearables, evaluate wearable computing more positively than average. For the present sample, the hypothesised moderating relationships H_{M1} and H_{M3} are empirically demonstrated by both the large effect sizes (f^2 = 0.018 and 0.021, respectively) and statistical significance of the interaction terms on a 1% level. On the contrary, as far as IT risk-related perceptions are concerned, neither innate consumer innovativeness nor the familiarity moderator exerts a significant effect on the focal risk-attitude relation. According to literature (Kenny 2015), results from the moderated regression analysis indicate that both interaction terms (i.e. *Innovativeness*Risk* and *Experience*Risk*) bring forth no meaningful change in explained variance of usage intention. This clearly runs contrary to the *a priori* theoretical considerations of the study. Thus, both moderatos may reinforce benefit perceptions rather than reducing salient risk anticipations. Since the risk-intention link is robust across the two interacting constructs, hypotheses H_{M2} and H_{M4} have to be rejected. Further detailed analyses are needed which might consider other potential third variables.

In sum, having critically scrutinised the obtained parameter estimates, this chapter corresponds to the empirical research objective of this thesis. In particular, the results of the structural model evaluation underscore the crucial role of cognitive beliefs and individual dispositions in motivating marketplace behaviours. By linking findings from factor and path analysis with the results from qualitative expert interviews, the final acceptance model is able to explain more than two-thirds in the variance of the endogenous variable *Behavioural Intention to Use Wearables*. The developed framework may thus be viewed as a valid instrument for explaining and predicting the adoption of wearable computing. To address the praxeological objective of research, the next chapter first derives managerial implications and then, finally, points out several limitations to this study in order to provide guidance and suggestions for future research.

8 Discussion of Results

This chapter is concerned with a general discussion on the contribution of the empirical findings to marketing theory and practice. Conclusively, the limitations of the present study are presented together with propositions for future research.

8.1 Synopsis of Research

In view of the significant business opportunities the wearable computing market is expected to create (cf. chapter 2.4), understanding user adoption behaviour of new wearable technologies becomes an economic imperative for management of companies. However, due to the emerging nature of the novel concepts of ubiquitous and wearable computing, extensive theoretical and empirical gaps still exist in Information Systems research. To fill these gaps, this thesis represents an initial study about the socio-psychographic acceptance factors of wearable computing and their nomological interdependencies.

In order to attain scientifically sound insights, this research project employed a hypothetico-deductive approach, linking conceptual, qualitative and quantitative research studies via methodological triangulation. Initially, the wearable computing phenomenon was systematised based on a thorough literature review in order to form a conceptual foundation. Then, through the exploratory study, single belief groups and traits have been identified as potential influence factors on the intention to use wearable computers. Since this qualitative research stage has proven to be highly useful for determining relevant consumer beliefs as well as for substantiating and refining hypotheses, this study provides clear grounds for applying methods triangulation in innovation acceptance research. According to Planing (2014, p. 269), a two-staged research process that sequentially gathers qualitative interview data and quantitative survey data is still a widely untapped methodological approach in the field. Overall, in the first phase of present research, seven semi-structured interviews with professionals from industry and from educational sector were conducted to gain preliminary insights into the research subject.

The qualitative results were discussed against the backdrop of the relevant literature and integrated into the newly developed conceptual framework, the 'Wearable TAM', that ultimately comprises thirteen behaviourally-relevant constructs. In terms of theory building, this study seeks to provide a new structural model by grounding the identified latent variables in a well-recognised general acceptance model (i.e. TAM) and applying them to a new context. Because the Wearable TAM combines the view of traditional innovation research with pervasive computing, IT security and personality psychology disciplines, it contributes to multiple literature streams. In particular, it allows researchers to jointly analyse consumer's beliefs about the trustworthiness, usefulness and security of wearables, the unique characteristics of the underlying pervasive computing paradigm, as well as the adopter's predispositions. The simultaneous investigation of such a broad range of product and adopter-related factors is still uncommon in most related studies on technology acceptance, which usually concentrate on functional product characteristics.

The proposed relationships were tested by following a post-positivistic research methodology. Thus, in the second research phase, a questionnaire was distributed among a random sample of 425 on-line panel members and 216

Internet users. The final population sample consisted of 474 respondents, yielding an effective response rate of 73.95%. In terms of representativity, a distinguishing feature of this study is its relatively heterogeneous sample covering a broad spectrum of diverse socioeconomic profiles. So far, empirical studies on IT adoption has frequently used smaller student samples as surrogate of consumers. However, since certain conditions suggest that students might differ from nonstudents, this has been considered a severe limitation to generalisability of results for both social and technological variables related to adoption (Kim & Peterson, 2017, p. 47; Ashraf & Merunka, 2016). By having such a diverse sample as in this research, it appears that there is sufficient variance in the constructs and that the results are thus generalisable to the target population.

In order to statistically assess the psychometric properties of the elicited success factors and to investigate whether the proposed correlative influences of the relevant users' traits and beliefs hold empirically, PLS-SEM was subsequently used as the best-fitting method for the analytical research objectives. After having evaluated the reliability and validity of the proposed measurement models, the findings from the inner model validation were consolidated to decide upon the confirmation or falsification of the theoretical hypotheses. In sum, the yielded parameter estimates allowed to generate reliable assertions about the role of the identified model predictors within the consumer adoption process in a wearable computing context. Focussing on the research questions set out in the first chapter of this thesis, in a next step the final conceptual model towards the acceptance of wearable computing was delivered and critically discussed. The new empirical insights substantially foster managerial understanding of the topic and provide concrete practical recommendations on how to overcome initial consumer's adoption barriers. The following sections thus focus on the implications for marketing theory and practice that can be derived from this research.

8.2 Theoretical Implications

This study advances contemporary knowledge in Information Systems research in several ways. Based on the exploratory interview study, single cognitive and personality-related factors could be identified that affect the perception of wearable technologies. The results were synthesised into a new conceptual framework on wearable computing acceptance, the Wearable TAM. Previous research contributions on the wearable adoption phenomenon are mainly of descriptive nature, which limits insights for theory building. The few existing path-analytical investigations draw primarily on single, generic base models in the sense of theoretical monism (see chapter 3.1). An integrated approach that exhausts the subject matter from a behavioural perspective is still lacking. The present research work thus contributes to the body of knowledge in that it provides a new behavioural model that is capable of explaining holistically the interpersonal decision to adopt wearable computing.

Motivated by the actual contrast between objective measures and subjective perceptions of IT security, the current research furthermore delivers empirical insights into consumer concerns about concrete security risks associated with wearable devices. In doing so, it bridges the gap between the traditional multifaceted conceptualisation of IT risk in security literature and its unidimensional measurement in most empirical studies. That way, it could be proven that privacy risks pose a major impediment to the rate of adoption in wearable technology markets, though system integrity can also be considered an important aspect. Interestingly, the data implies an inconsistent mediation model es regards the first-order constructs perceived availability, perceived integrity, and perceived

confidentiality. Specifically, system integrity perceptions appear to possess a suppressor effect on availability perceptions which is a unique insight into subjective information security assessment. From a path model point of view, this research could confirm a recursive linear relationship between trust as an exogenous and IT risk perception as a negatively affected endogenous construct. Another interesting study finding is that contrary to expectations neither personal innovativeness nor experience does show any significant moderating effect on the relationship between perceived risk and behavioural intention. This certainly deserves further attention in technology acceptance research.

Unlike most empirical works with similar theoretical focus, based on a consumer value perspective this research further advances knowledge on usefulness perceptions by combining a series of utilitarian beliefs into an index representing the wearables' positive usage consequences. This allowed to identify the perceived support of health and fitness as a 'success factor' that primarily drives usefulness perceptions of wearable computers. Also, to calibrate the research model to the particularities of the study object, issues concerning a new pervasiveness construct including its conceptual properties, constituents and effects were considered, an approach not previously undertaken. It could be shown that unobtrusiveness is the most important pervasiveness dimension that indirectly affects the intention to use wearables, which is an unprecedented finding in Information Systems research. However, according to study results, system pervasiveness characteristics have to be translated into concrete application scenarios that are perceived as beneficial in order to become behaviourally relevant.

In addition, by incorporating personality-related correlates within the synthesised nomological net, this thesis contributes to contemporary research on the role psychological predispositions play in the technology adoption process. Specifically, the effect of the well-established *Big Five* personality dimensions on the intention to use an innovative technology is still an underdeveloped area in the chosen field. In order to be able to investigate traits at each level in the personality hierarchy of behaviour, the 3M model was applied. Albeit this framework has been used in several consumer research contexts including compulsive buying (Mowen & Spears, 1999) and travel behaviour (Scott & Mowen, 2007), online shopping (Bosnjak, et al., 2007), volunteering (Mowen & Sujan, 2005), word-of-mouth communications (Mowen, et al., 2007), online social shopping (Kang & Johnson, 2015), and financial satisfaction (Davis & Runyan, 2016), it has not yet been applied to technology adoption. In particular, this study could shed light on the great significance materialistic values and agreeableness have on affective involvement towards innovative technologies. Yet, one remarkable finding is that the effect of the latter elemental trait is particularly strong in the male subpopulation. In regards to the causative impact of the conscientiousness trait on NFC, the empirical results clearly disprove its exploratory role in a technology acceptance context.

Still, only little is known about the facilitating conditions of wearable technology usage. In an effort to deepen the established understanding of the attitudinal dependencies, this study also investigated the contingencies that underlie the relationships between usage intention and its cognitive causes. More precisely, two salient moderator variables, which emerged during the conceptual and exploratory research stage, were integrated into the model to elevate its explanatory power. As mentioned above, their moderating influence does only hold for the perceived usefulness-intention link, which helps increasing the predictive power of the hypothesised structural model. Beside this, relevant demographic control variables were also considered to check the robustness of the formulated system of hypotheses. In the course of the multigroup analysis, generational cohorts in terms of *digital natives* and *digital*

immigrants emerged as promising background variables that are particularly worthwhile giving further investigation in an information technology acceptance context. Consequently, this study adds to extant literature on socio-demographic differences in individual technology adoption, as well.

8.3 Managerial Implications

In order to remain competitive in the fast-paced technology sector that is characterised by increasingly shortened product life cycles, enterprises must constantly strive to create innovative products which deliver new customer value in the marketplace. The significance of ICT-based innovations becomes particularly apparent in the case of the mobile phone industry: In many cultures, e.g. Apple iPhone has nowadays transformed into a platform for self-expression and social learning, taking on greater emotional importance in people's lives (Morris & Aguilera, 2012, p. 622). In a similar vein, technological advances including new sensors and low-power radio chips has led the consumer electronics industry to believe that wearable computing will be 'the next big thing' (Hunn, 2015). However, unlike smartphones, wearables clearly fail to grow at forecasted rates and still struggle to gain momentum beyond innovators (see chapter 2.4). To achieve market penetration more quickly, innovation research emphasises the pivotal role of social acceptability in commercialising new technologies. Considering that wearables' business models are typically built around 'technology push' rather than around market needs (Topor, 2016, p. 381), identifying socio-psychological success factors becomes even more crucial to cross the chasm between early market and mainstream market customers. Therefore, the implications derived from this study are of practical importance for wearable manufacturers and other strategic partners of the wearable technology ecosystem alike.

Since the 'willingness to use' an information system has repeatedly been proven to serve as a proxy of actual adoption behaviour in prior research, consumers who score high in wearable usage intention may be deemed the target audience for the wearable industry (cf. chapter 3.1.21). According to present study results, it is noticeable that both cognitive and affective responses strongly covary with usage intention. Still, cognitive information processing comes more to the fore in the context of wearable computing adoption. In line with numerous prior Information System studies, the empirical investigation thereby corroborates the dominance of cognitive beliefs in attitude formation. From this it can be concluded that wearables actually represent high-involvement products. As opposed to low-involvement products that are typically subject to routine response behaviours based on limited information, they are rather purchased after careful consideration. Thus, the primary goal of innovating companies should be to affect the cognitive component of users' attitudes. Vendors should concentrate more on informative issues in their communication-mix than building brands with less informative advertisement. For achieving susceptibility to persuasion, consumers need to be educated about the product's main attributes by means of comprehensive, issue-relevant information delivered in a logical, verifiable manner (cf. Chen et al., 2007, p. 1048, and Ha, 2002). Due to their rational purchase motives, wearable technology consumers may be deemed more willing and capable of processing new, product-related information via the central rout to persuasion. As a result, they are more likely to be persuaded by rational claims and product-inherent value message arguments. Thus, providing easy available means-end information may reduce consumer search costs and facilitate decision-making.

However, wearable technologies are still hardware dominant innovations and the majority of consumers consider wearables to be of limited usefulness. In the first instance, marketers should therefore give priority to the development of more compelling service models to drive greater adoption. Particularly, the conducted field study accentuates the relevancy of software innovation for hardware success, in that the hardware-enabled pervasiveness of devices has a smaller total effect on usage intentions than compared to application-based benefits. Consequently, it appears worthwhile for device makers to develop innovation networks, strategic alliances or joint ventures with software, content and service providers across the value chain. This enables the individual actors to concentrate on their core competencies and to access new markets and value potentials. In this context, Swiss watch manufacturer TAG Heuer may be alleged as a positive example, who partnered with Google and Intel to move into the smartwatch market with a luxury Android wristwatch (TAG Heuer, 2015). Another example would be the German optical manufacturer Carl Zeiss AG, who just recently announced future collaboration with Deutsche Telekom in the field of smart glasses in order to ensure network connectivity of their smart lens prototypes (ZEISS Group, 2017). The company thereby strives to develop data glasses which feel and look like usual eyeglasses.

As demonstrated by the survey data, perceived support of health and fitness appears to be the core reason to date why consumers are interested in adopting wearables. This underlines the tremendous entrepreneurial and economic opportunities for the health and wellbeing sector. Since the expected enhancement of personal abilities emerged to be the second strongest driver of usage intention, software developers and service providers should focus their attention on devising tailored applications that improve efficiency, productivity and engagement across different industries such as healthcare, fitness, retail, travel and entertainment. Advertisers should highlight the role of functional benefits for users in improving their lives at home, work or recreation. They should help prospective users envision how wearables can make everyday tasks more effective and enjoyable. For instance, health and fitness applications might engage users with incentives and gamification to create easier means to achieve goals, while e.g. retail apps could deliver a more integrated shopping experience with stronger shopping insights and faster payment, as proposed in (Gartner, Inc., 2016) and (Bothun, et al., 2014). To be considered efficiency-enhancing tools, wearables should not just provide data that is informative, but also real-time information that is prescriptive (Bothun, et al., 2014). That is, in order to offer some tangible value-added, advanced analytics should help users to turn insights into specific actions, ultimately leading to efficiency gains or changes in behaviour.

Behavioural relevancy of individual benefit expectations, however, is significantly affected by both experience with wearables and personal innovativeness in the domain of information technology. The more individuals gather experiences with wearable technologies, the more positively they will evaluate these devices. Thus, frequent product demonstrations and pre-purchase trials appear suitable as they can give a vivid impression of the benefits of wearable computing. According to Rogers (2003, p. 16), innovations that can be experimented on a limited basis are generally adopted more rapidly. This also implies that these smart gadgets will more likely pervade and accompany everyday life when companies fund wearable computers for their employees, rather than implementing a BYOD model. In addition, since usefulness perceptions show a higher predictive power in innovative population segments, target-group oriented marketing campaigns seem promising. Innovators may serve as key change agents and opinion leaders to foster further diffusion of wearables (Agarwal & Prasad, 1998, p. 205). When implementation resources are scarce, targeting this segment renders particularly efficient. Of course, marketing efforts should be directed to those on-line and offline paths of communication, which possess the highest

probability of consultation by the target audience (Broilo, et al., 2016, p. 207). In case of innovators and early adopters, particularly on-line communication channels such as social media platforms are likely to lead to success (Pagani, et al., 2011, p. 449).

For wearables to be perceived as useful, they should provide unobtrusive anytime-anywhere access to actionable data and relevant computing resources in a context-aware manner. Ultimately, it is the great degree of system pervasiveness that opens up a new frontier of immersive user experiences and market opportunities. The 'pervasiveness' characteristic uniquely distinguishes wearable computing from traditional Information Systems paradigms including ubiquitous and mobile computing. In doing so, it delivers a distinct value proposition (i.e. relative advantage) that may not be derived effectively through alternative means such as smartphones. In a nutshell, wearables are supposed to be continuously worn and support their users on-the-go, why they should be as natural and unnoticeable as possible in various social settings. This clearly reinforces the significance of human-centred design principles, which aim at incorporating human factors in very early stages of technology development (Motti & Caine, 2014, p. 1820; Rekimoto, 2001, p. 21).

Furthermore, the assessment of *Perceived Pervasiveness* components indicate that unobtrusiveness of devices is the least developed dimension presently. Therefore, in addition to design and form factor, which may account for a wearable's physical 'invisibility', technology manufacturers should specifically address issues of communication modalities (i.e. tactile, visual and auditory) to increase unobtrusiveness (Karaiskos, 2009, p. 93). Input/Output modalities should ideally converge upon implicit human-computer interaction, whereby a system infers implicit input from current context (e.g. location information, user activity, skin sensitivity, etc.) and proactively outputs a relevant action without distracting the user (Fedosov, et al., 2016, p. 150; Yavuz, et al., 2014, p. 279).

Another valuable insight from the present study is that providing tangible benefits is much more important to reach mass adoption than controlling information technology risks. Nevertheless, security concerns turned out to be a significant obstacle to wearable acceptance. Thus, companies should provide high-risk perceivers with informative advertising and risk-reducing cues such as corporate credibility. The security of wearables with regard to information confidentiality, integrity and availability needs to be clearly communicated. Prospective adopters need to be reassured of a strong security infrastructure (e.g. network security, encryption, strong authentication and defensive measures) as well as the vendor's openness and integrity (Featherman, et al., 2010, p. 229). Service providers are therefore encouraged to display clearer explanations and visualizations of security protection measures and polices to reduce consumer apprehension and latent uncertainties.

In particular, survey data show that potential breaches in privacy represent the greatest risk consumers face when confronted with wearable computing. Consequently, vendors may gain a competitive advantage by improving consumer attitudes towards their privacy practices. A high level of *transparency* about the use and protection of data gives users a feeling of control over their personal information. Hence, especially in times where costumer data is a growing source of competitive advantage, market actors ought to be consistently transparent on what personal data they collect and how and when they use it. A recent consumer survey shows that when personal data is used to improve a product or service, individuals generally feel this would be a fair trade for their data (Morey, et al., 2015). Therefore, companies should openly communicate what value, if any, customers receive in return for their data and, moreover, integrate privacy considerations into product development from the very beginning.

Furthermore, as the quantitative study shows, security concerns are heavily affected by trust in wearable computers as regards system functionality and predictability. Building consumer trust appears therefore to be key in reducing uncertainties towards innovative technologies. Since a system's reliability may not be perfectly observed prior to product testing, it can be regarded as an *experience quality* (Dierks, 2005, p. 59). This reaffirms the relevance of free trial periods and product demonstrations to give adopters opportunity to try the technology and to develop comfort. In regard to communications mix, interpersonal sources of marketing messages are perceived as more trustworthy than commercial ones. Particularly informal message initiators such as friends, relatives, members of a reference group, and so forth, are seen as comparably credible sources, since there already exists a relationship of trust among peer consumers (Foxall, 2014, p. 99). This clearly emphasises word-of-mouth (WOM) over just conventional advertising. In respect of the target audience of innovative, relatively technology-savvy digital natives, electronic WOM (eWOM), whereby message dissemination takes place on-line (e.g. in social networks, blogs or brand communities), appears specifically effective.

Another way to overcome initial adoption resistance is to disseminate communication messages that are not just informational (i.e. factual and meaningful), but also transformational (i.e. affect-based) as suggested by the evidenced conative influence of affective involvement. Under affective involvement conditions, both perceptually salient cues (e.g. visual and auditory aspects) and message content must be presented in a consistent and coherent fashion to foster mental image creation. Hence, messages communicated to facilitate wearable adoption should balance informational and transformational content to reach market involved consumers. Furthermore, current research indicates that a favourable attitude towards innovative technologies is significantly determined by dispositional motives. Both need for material resources and need for cognition were identified as being important internal antecedents of marketplace behaviour. As compared to the latter personality correlate, materialism has more pronounced affective aspects (Bosnjak, et al., 2007, p. 600). Materialistic individuals are generally characterised by high scores on social influence and status consumption (i.e. acquiring goods for the status they confer). To display status, they often use branded products (Flynn, et al., 2016, p. 763). Given the strong correlation between brand engagement and materialism, marketing practitioners should pay particular attention to long-term brand development and brand communication as a means to appeal to the high status to be gained through product purchases. Brand alliances might also be used to link less-known brands to established trademarks that do confer status (Ueltschy, et al., 2011 p. 91). More specifically, during multi-group comparison the materialism-affect linkage was found to be stronger in the male subsample. Likewise, gender-related patterns emerged in the development of materialistic attitudes, since the negative impact of agreeableness on materialistic values is only significant for men. In conclusion, marketing efforts that address materialistic traits should primarily appeal to male consumer segments.

On the contrary, consumers high in need for cognition are more attitudinally influenced by argument quality and cogency of claims. This cognitive personality characteristic has received much interest from marketing researchers since it enables deduction of various valuable implications for advertisers. For instance, individuals who enjoy cognitive tasks are more likely to be responsive to product-related information and description of an ad (Schiffman, et al., 2009, p. 147). Also, they spend more time browsing the Internet to seek product information and they are more likely to processes print advertisements as well. Furthermore, a between-subjects factorial study demonstrated that for consumers high in need for cognition ad persuasion increases with *conclusion implicitness*

(Martin, et al., 2003, p. 64). This means that implied arguments in advertising that allow more scope for individual interpretation such as “compare for yourself” prompt higher levels of message processing and thus involve rather high-cognition inclined individuals. More recently, an empirical study using a Taiwanese sample shows that the effectiveness of diagnostic product information in marketing messages (e.g. comparative advertising and information about other consumers’ ratings) varies as a function of the recipient’s tendency to engage in effortful thinking (Chang, 2007, p. 82). This implicates that advertisements for wearables which are designed to appeal to the high need for cognition consumer should incorporate diagnostic information and more implicit conclusions where appropriate.

Recognising the diversity among potential adopters, promotional applications ought to be sensitive to individual differences in consumer approach behaviour. Distinct consumer needs necessitate clearly differentiated product offerings and strategic targeting to be met economically. Therefore, consumer markets should be divided according to (personality) profiles that are profitable. For example, Mulyanegara et al. (2009, p. 12) propose to implement personality-based segmentation by promoting different types of brand personalities to target different subgroups of consumers. Present research provides tentative evidence that individuals who score high in neuroticism are more likely to have a materialistic value orientation. Hence, to attract consumers with neurotic tendencies, a company’s brand might be positioned as trustful and reliable. In addition, the study provides support that extroverts are more inclined to actively engage in cognitive information processing. As individuals who are dominant in extraversion tend to be gregarious and conversable (Lucas, et al., 2000, p. 453), marketers may position their brand as being sociable. They may also employ outgoing salespeople and shop assistants as a promising means of in-store merchandising.

To sum up, the managerially oriented implications derived from this research are substantial and may help to develop more efficient communication-mix strategies in order to increase public acceptance for innovative wearable technologies. Also, the identified effects of user diversity which were found to strongly affect acceptance judgments highlight the significance of a more differentiated market development. In closing, it should be reemphasised that smart wearable devices offer enormous business opportunities to enterprises. Not only new markets can emerge, which find innovative ways of monetisation, e.g. through targeted wearable advertising, but also previously unlikely alliances could be formed between different manufacturers, component suppliers and service providers. The new type of technology might substantially modify media usage and interaction between companies and customers in the near future. Wearables may even support a behavioural change on societal level through feedback cycles and continuous monitoring capabilities, which certainly poses a promising connecting factor to other research areas such as big data crime prevention and prediction. Yet, since network effects likely accelerate diffusion of wearables across relevant consumer markets (see chapter 2.4), it is vital for vendors to attain soonest possible a critical mass of customers. Understanding consumer perceptions that drive an early adoption of wearables is therefore of particular praxeological importance to device makers and may significantly catalyse diffusion of the innovative computing paradigm.

8.4 Limitations and Directions for Future Research

Even though this study makes several theoretical and practical contributions to existing knowledge in Information Systems research, there are some limitations due to the research focus (applied methodology, region, time, and type of innovation) which must be considered when evaluating the reported results. By its very nature, a limitation establishes an inherent weakness of a study, but simultaneously provides a valuable avenue for future academic efforts. Therefore, both key limitations of the work undertaken and further research needs are addressed in the following.

8.4.1 Limitations

Firstly, as with most qualitative studies, the inductive insights gained through exploratory expert interviews might be subject to interviewer bias. This means that interviewee responses might be distorted by the existing attitudes and beliefs of the interviewer. For example, the wording of a particular question can impact the type of answer the respondent gives (Groves, et al., 2009, p. 292 ff.). Therefore, it remains unclear whether the exploratory findings would differ if other investigators had been employed. To prevent this effect as far as possible, semi-structured interview guidelines were used, which bring some level of consistency to the interview situation, though offering the flexibility of a free dialogue. In addition, the qualitative results were largely substantiated through quantitative validation of derived theoretical assumptions, which is why the results can be regarded sufficiently intersubjective. As regards the demographic characteristics of the interviewees, it is furthermore worth noting that due to the theoretical sampling strategy only male individuals were represented in the qualitative study. Even though the sample adheres to the *a priory* defined sample characteristics (i.e. the participants were particularly familiar with the study object, cf. chapter 4.2.1), it should be acknowledged that the gathered perceptions might be latently subject to gender bias.

Secondly, a disadvantage of any cross-sectional research is that it is susceptible to common method variance. As outlined in chapter 7.1, method bias might has inflated the strength of the correlations under scrutiny. In spite of both the implemented ex-ante remedies to control for artefactual covariation (e.g. pretesting of online questionnaire) and the results of Harman's single-factor test, the occurrence of a systematic method error cannot be completely ruled out. Future research could solve this issue by e.g. employing multiple data sources or periods of data collection. In this context, fellow researchers are also encouraged to examine continued wearable usage behaviour by means of a longitudinal study design that extends the measurement beyond one point in time. It would be revealing to see how intentions and attitudes change over time with increasing or decreasing frequency of usage. Further sources of heterogeneity could be investigated that require more knowledge of the respondents such as hedonic and social aspects to examine complementary acceptance parameters at later stages of wearable adoption.

Thirdly, with respect to the empiric data analysis, a common criticism is that any form of correlational model cannot conclusively confirm any causality (Hair, et al., 2016 p. 15). As Westland (2015, p. 147) concluded, "model predictions can only be considered plausible, rather than confirmed by the data testing." To address this issue, all causal hypotheses were based upon strong theoretical and empirical grounds, drawing on a series of qualitative

interviews and comprehensive literature review. A further critical point is that causal models such as the Wearable TAM generally simplify complex relationships as linear relations. However, structural models might also be non-recursive, i.e. they can contain circular relationships between latent variables. For instance, prior research suggests that conscientiousness and need for cognition mutually influence one another, what questions the implied endogeneity of the latter construct in the current conceptual framework. From a technical perspective, PLS-SEM is intrinsically not able to deal with such causal loops (Hair, et al., 2016 p. 18). Considering that among any given structural theory several alternative models potentially exist that are equivalent in terms of overall goodness-of-fit (Chin, 1998b, p. xii), conceptualising alternative candidate models that may contain more complex relationships and comparing them with the aid of CB-SEM could help to gain better insights. SEM literature recommends to search for different predictor structures via a step-by-step approach to model creation that uses the same data in each step, e.g. by post-hoc modifications such as eliminating insignificant pathways or adding new relations as suggested by modification indices (Gross, 2014, p. 233).

Fourthly, it has to be acknowledged that the research had a national focus on Germany for both the qualitative and the quantitative part. Potential effects of culture-specific attitudes hence remain unexplored. This empirical setting might pose a threat to external validity, as pertinent research works frequently reported a significant impact of socio-cultural differences on the acceptance of innovations (e.g. Bagozzi, 2007, p. 248). This applies all the more to personality-related variables such as extraversion and agreeableness, which have been proven to be particularly sensitive to 'cultural effects' in previous studies (Gurven, et al., 2013 p. 355). Therefore, it is questionable whether the study results are readily applicable to other geographical areas. In order to broaden the basis for empirical evidence and to alleviate cultural bias, future research is encouraged to extend the scope of the current survey design to further localities such as the U.S. market, where penetration of smart glasses has already begun. Moreover, this thesis has a clear defined research subject (i.e. acceptance of wearable computing). Pertinent literature, however, indicates that findings in the field of technology acceptance can never be transferred directly from one context to another without any adjustment (Planing, 2014 p. 276). It is very likely that any other individual research context would have yielded slightly different analytical findings. Thus, to provide insight into the generalisability of the developed nomological structure, this study should be replicated on further markets and related technological areas in the context of ubiquitous and pervasive computing (e.g. smart home appliances or connected car). Similarly, a final limitation revolves around the chosen technologies (i.e. smartwatches and smart glasses) as test objects of study. Since the underlying conceptual framework was designed to be relevant and applicable to other wearable technologies, additional insights could be gained from broadening the research setting to further types of wearables such as smart jewellery or smart clothes. As wearables represent just a small, but dynamically developing part of an "emerging larger cohesion widely known as the 'Internet of Things'" (European Commission, 2016 p. 4), only experience will show which form factors and applications will dominate the future of wearable computing.

All in all, more studies need to be done under varying conditions to elaborate wearable computing adoption in greater depth regarding different applications and subpopulations, so that a comprehensive picture can be drawn. Nonetheless, considering the scarce resources of this study, the applied research design and methodology can be regarded appropriate and efficient. As could be shown, this thesis provides a strong contribution to theory and practice in spite of the named restrictions. Also, the pioneering character of research has to be stressed, too.

Throughout the course of this thesis, it was referred to the early stages of wearable computing diffusion and the resultant extensive research gaps. This leaves ample room for further academic endeavours. Specifically, some findings of the current study pose new interesting issues, which go beyond the actual investigational scope. Therefore, the next sections discuss propositions for future research activities.

8.4.2 Avenues for Future Research

This thesis represents a first comprehensive study entirely dedicated to the emerging phenomenon of wearable computing adoption. Due to the clearly defined study focus, several knowledge gaps in related fields were identified, which should be addressed by future large-scale efforts. The following subsections delineate the most striking issues from a conceptual angle.

To date, the prevalent perspective for explaining user attitudes towards information technologies is still cognition-based. However, an interesting analytical finding is that acceptance judgments are not only determined by cognitive beliefs, but also significantly shaped by the personal importance attached to the new type of technology. This strongly supports the call of recent Information Systems research to take greater account of the emotional nature of Information Systems usage (Leger, et al., 2014, p. 466). The demonstrated effect of involvement extends the cognitive concept of conative attitude by a further explanatory dimension and, in doing so, increases informativeness of the *explanans*. Since product involvement reflects a quite enduring motivational state of arousal and interest that strongly relates to repeat purchases (Blythe, 2013, p. 89), the gained survey findings are of special significance for future innovation research in the field. In particular, the observed collinearity among the measures of involvement and adoption decision bears witness to the conceptual proximity of affective and cognitive appraisals. Thus, a promising approach would be to merge affective involvement (in the sense of attitude strength) and behavioural intention into a more general higher-order construct that mirrors the cognitive-affective structure of conative attitude. Furthermore, the relatively weak R-squared value of 0.112 for involvement suggests that there are other important factors influencing affect-laden consumer responses besides the personality-related variables included in the research model of this study. Future replications should therefore try to develop a better understanding of the involvement phenomenon by considering further potential antecedents. A starting point for the identification of involvement sources may be the influential work of Laurent and Kapferer (1985), who identified five antecedent conditions including perceived pleasure and perception of sign value (self-expression or self-identity).

Regarding the operationalisation of the Big Five personality traits, further inventories should be taken into account. The ultra-short BFI-10 scale of personality structure that was employed due to resource constraints delivered only weak internal consistency results. Confirmatory factor analysis revealed low alpha reliabilities ranging from 0.410 to 0.663. Here, it should be reemphasised that even elemental traits are commonly assumed to possess a hierarchical structure with each individual personality domain being comprised of several sub-facets (Costa & McCrae, 1995, p. 21; Credé, et al., 2012, p. 876). Thus, there is reason to suspect that two-item scales could fully capture the breath of a specific personality domain. In addition, in measurement theory brief measurement instruments with less than three items are considered not suitable for latent factor modeling (Maroof, 2012, p. 31). Since problematic items were dropped in the course of scale validation, data integrity might be even more

compromised. Given these psychometric concerns, if greater resources are available, future research should make use of more comprehensive inventories of personality such as the original standard BFI-44 scale as described in (Benet-Martinez & John, 1998). By enabling a higher level of detail, this instrument is more predictively capable, which is important for an accurate psychographic market segmentation.

Furthermore, the multigroup analysis evinced that individual difference variables (i.e. specifically age subcultures) significantly interact with IT-related risk perceptions. Due to conceptual limitations (the Wearable TAM strives for parsimony at the cost of accuracy), only a few salient demographics were employed to disaggregate the risk-intention relation for the sake of increased variance explained. However, a growing body of literature broaches the issue of heterogeneity in security risk perceptions and attitudes (cf. Joo & Hovav, 2016, p. 109). It is thus quite likely that further contextual variables have an effect on this relationship. Moving beyond the present theoretical framework, further effort should be made to enrich current understanding of contextual dependencies of IT risk perceptions. For example, Chi et al. (2012, p. 99) empirically demonstrated that under the interactive effect of perceived risk and subjective norm, usage intention gradually diminishes. In contrast, Colobran (2016, p. 2) assumes that the degree of security knowledge strongly modifies subjective security perceptions. In light of the study results and under the premise that digital natives are typically more computer literate, incorporating IT security expertise as an additional grouping variable into the structural model appears particularly worthwhile.

Finally, it should to be stressed that this study makes no claim to completeness. The empirical findings in support of the hypothesised structural model do not preclude the acceptance phenomenon from also being explained by other latent variables. As stated by Yang et al. (2016, p. 267), owing to their possible visibility to others (which depends on product type), many wearables are both high-tech electronic devices and fashion items at the same time. Therefore, it would seem informative to know how e.g. brand experiences or aesthetics and design perceptions interrelate to the adoption predictors. Further in-depth investigation that considers additional explanatory variables is needed to produce a holistic understanding of innovation adoption in the area of wearable computing. In view of the fact that research on wearable computing is still in the early stages of its development, reconceptualization of composite constructs may also be considered in prospective research endeavours to ensure content validity. For instance, perceived authentication and authorisation mechanisms might be important criteria in the consumer's overall valuation of the security of ultra-mobile devices, as discussed earlier in chapter 2.3. Moreover, when looking at the benefit side of the evaluative judgement, it should be acknowledged that the employed scale on perceived usefulness was established at the time of research. Therefore, the construed index naturally neglects potential future usage scenarios that may translate into relevant utility dimensions. However, only time will tell which exciting new applications and ensuing benefits might emerge in fields as diverse as emotional communication and telemedicine. In order to elicit consumer preferences, conjoint analysis might prove useful. Jaeger et al. propose in (2013, p. 3682 ff.) to use PLS regression for analysing interval-level conjoint data. From a methodological standpoint, this would be an interesting rout for future research.

As shown, wearable computing represents a promising new field of study. Even though this thesis provides some valuable insights, a lot of questions remain unanswered to date. The new issues raised by the current work will hopefully inspire other scholars to further explore the interesting phenomenon from a consumer perspective. In

light of the continuous evolution of new wearable devices, however, it is reasonable to expect that in the future wearable computing will receive even more attention from researchers and practitioners alike.

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Appendix

A.1) Interview Guide

Research Project: **Acceptance of Wearable Computing**

Institution: **School of Computing, Electronics and Mathematics, Plymouth University**

Interviewer: **Lena Gribel**

- Entry to subject area
  - We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you personally? And what role do wearable technologies play in your company? What technologies are utilized for what purposes?
- Assessment wearable technologies
  - What is your assessment regarding the current development of the wearable technology market? What market potential do you see?
  - What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?
- Wearable technologies in companies
  - What insights did you gain about wearables in respect of customer relevance and productive use?
  - What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?
  - What in your opinion are the main incentives for integrating such technologies in everyday life? Please sort the following topics by relevance ranking:
    - i. Boost of personal abilities,
    - ii. Improvement of health and fitness,
    - iii. Boost of self-confidence,
    - iv. Helps feel more in control of personal life,
    - v. Enhancement of social relationships.
  - What do you expect from wearable computing solutions? What functionalities are of major significance, e.g. certain sensory features or context-awareness?
  - What risks have to be addressed in particular (e.g. functional risk, economic risk, social risk, IT security risk, etc.)?
  - In your opinion, what changes of behavioural habits are likely to occur? How do you assess the significance of the wearable computing phenomenon for society?
- Closing question
  - First of all, thank you for your information! Would you like to discuss any further topic-related issues outside the matters raised so far?

A.2) Interview Transcript 1

We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you as a professional? And what role do wearable technologies play in your company? What technologies are utilized for what purposes?

Personally, a relatively small role, as there are no real application scenarios yet in a company context where we actually use wearables. But in our company, there are now diverse activities that are slowly leading us in this direction. We realise that wearables represent a technology which surely will widely disseminate on the market and it is thus important to deal with this subject generally. We now have developed a first application that lets you, for instance, park a car by means of a smartwatch. However, there are furthermore diverse thoughts for e.g. production support in industries; capture things by the use of wearable technologies, that is to accelerate processes, but also to capture the state of the employees. Indeed, the topic ‘health’ is something that in agreement with the works council sooner or later will become a very interesting matter, but also the topic ‘support’, that is, the application of wearables in the daily doing is quite promising. There, wearable technologies will be extremely useful for sure.

What is your assessment regarding the current development of the wearable technology market? Can you see there any market potential?

Yes, indeed. There are certain products that actually, upon closer inspection, seem more promising than they actually are. However, the issue sensor technology and wearables - everything that doesn’t heavily depend on the shell of man - possesses market potential.

To me, glasses are not that promising, as their technological level still is fairly low. It depends on the person wearing the glasses; for example, visual impairments, different proportions and so forth should be considered. This does not hold for smartwatches or smart wristbands since they can be used comparatively freely.

What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?

Smartwatches, wristbands. Further on, there are also smart rings for controlling and diverse sensory that gather data from the person him/herself.

What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?

None of these aspects of use, neither nor. I think this is because people have understood that even smartphones are already complicated devices. I mean, it’s like this: They are not made in a way that one continuously checks them, they don’t provide hands-free working; at least one hand is always blocked and information is comparably difficult to access. I mean, in the meantime there are people who perceive their smartphone’s vibration in the pocket where there is no actual vibration. Then they get their phones out of their pockets and take a look and if there is no call or notification they put it back in the pocket what is clearly very cumbersome. Even though these devices are always carried around, they are not fully integrated into the working environment. They continue to represent foreign objects and, in some situations, even pose a danger. For example, at hazardous workplaces, where staff

have to climb a ladder in order to measure something by electronical device. Traditionally, these devices have to be get out of the pocket first, what might be very dangerous. Against this backdrop, wearables offer more security. Things become just very much characterised by technology by now. People realise that things become simpler by means of technologies. Thereby, information can be accessed quicker and easier. That information can be rapidly accessed is particularly interesting from a company perspective, as well.

For example, a study of a German automobile manufacturer: two productions lines had been set up and the new products had supported the processes differently:

- number 1 with a smart glass (primarily for documentation)
- number 2 with a smartwatch

It has been shown that on average four mistakes in the production could be reduced to 2,2 errors with smart glasses and with smartwatches even up to 0,8 errors, simply because there was support regarding which step had to be performed next. Thus, efficiency enhancement has been generated within the frame of the process. The smartwatch has helped the employees without impeding them from work. It is also clear, that there are reservations which hold also for the smartphone, for instance that it would be just a toy. Also, personal data pose severe concerns as well as IT security threats. In addition, hygiene factors are relevant, for example in the course of varying work shifts where employees have to share one pair of smart glasses this probably would be a problem.

What in your opinion are the main incentives for integrating such technologies in everyday life? Please sort the following topics by relevance ranking:

I. Boost of personal abilities,
II. Improvement of health and fitness,
III. Boost of self-confidence,
IV. Helps feel more in control of personal life,
V. Enhancement of social relationships.

From the point of view of a company, boost of personal abilities is absolutely important in specific areas. Permanent Control: if a process gets boring, it sometimes is too bothersome to look explicitly at the instructions once more. The easier an information is accessibly the more likely it is that you look a glance once again and that mistakes are avoided. Our workplace is becoming more and more complex; people have to cope with new tasks that are no more ordinary. For example, if one has to check an object whether it is working or not and, at the same time, processes are still not internalised, then such information concerning what to do are very valuable. In other words, enhancement of proficiencies and benefits of reduced workload; you have always your instructions with you and can browse it rapidly where necessary.

Social relationships if related to communication in a wider sense may be enhanced as well. This short chat-based information would be interesting, that is if you could have relevant information sent to you in real time.

Improvement of health and fitness goes along the lines of fitness, what isn't of relevance from a company's viewpoint. Health should be considered as a separate aspect.

Hopefully, wearables will be given to those people who need them, especially in financial terms. We need to get away from a society which conceives the iPhone as awesome. This is a work equipment and if an employee gets a watch it is not meant as a means of expressing oneself, but rather it serves to optimise his/her processes and if he or she thereby gets more self-confidence it would be not the prime objective from a company's view point. Social relationships should be treated with caution; sure, there are companies which consider this, but only a few in Germany. From a company perspective, I would thus focus primarily on the enhancement of abilities.

In your opinion, what changes of behavioural habits are likely to occur? How do you assess the importance of the wearable computing phenomenon for society?

I am very much in favour of the idea of gamification and I could image that if one succeeds in analysing the basic human vital signs that it would be of great benefit to be able to challenge with others, as people could live report everything. Or in the area of health: that for specific professions the workload would be captured without the need for monitoring, so that their work environment can better be organised. It could lead to a mergence of private and business life and we would have to face the challenge that people would use wearables in private life, as well. The problem here is that companies would have access to personal data. These are the considerations one must face. It would be a nightmarish thought if a company would know about all employees how long and how well he/she has slept; this would be this surveillance phenomenon regarding the privacy risks.

A.3) Interview Transcript 2

We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you as a professional?

It is interesting what progress we have made here. At the moment we have mobile phones and laptops. Wearables are very important to me. Yet, their development is at the beginning. We have to wait and see what the future holds and how acceptance could be developed in the population; and will wearables be affordable for all end consumers or will we see them only in the professional sector.

And what role do wearable technologies play in your company? What technologies are utilized for what purposes?

At the moment we don’t sell many, but we are gearing ourselves to a future where the field of wearable computing is much more extended.

What is your assessment regarding the current development of the wearable technology market? What market potential do you see?

I can see a great market potential for wearables, but as I said, wearables like Google Glass are crucially contingent upon the pricing structure. Everything that goes beyond 1.000 € won’t function for sure. If we succeed to manage wearables which are in the 300 € range, what we had experienced with tablet PCs, then they will assert themselves. Sometimes the banal principle of Microsoft suffices, where the product matures on the customer’s side […] then I think that the development needs to find its way.

What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?

Social aspects, i.e. definitely the topic styling. I don’t think that you can assess this under an exclusively practical point of view, as can be seen from the success of Apple’s Iphone. Not the most important product on market wins, but rather the product with the greatest innovativeness; what moreover, let me put it like this, is effective as good publicity. Well, I think that Microsoft has done well with its HoloLens. They have realised that the soft factors particularly make a decisive contribution to the acceptance of the product. In the end, the topic is pretty complex, lying in a grey zone, so that the question can’t be answered by yes or no.

What insights did you gain about wearables in respect of customer relevance and productive use?

You can notice that the customers are very curious and want to participate. However, as I said above, Microsoft got on its knees with its Google Glasses; since then, they have become much more cautious.

What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?

In any case smartwatches, as they have already been established and it represents a fashion product. This fits very well into contemporary times. I guess that in future more will happen with smart glasses.

What do you expect from wearable computing solutions? What functionalities are of major significance, e.g. certain sensory features or context-awareness?

That prices will be favourable, that is, that they will become affordable and that they will fit well into the personal lifestyle. Besides, they should be based on standards; however, one still doesn't know in which direction they will develop. For example, by means of the HoloLens many peripherals could be eliminated; all monitors, all displays, all that stuff could be left out. Iphones and stuff could be left out. This would bring much development potential and cost-saving opportunities at other points. Yet, it requires a certain standardisation upon extant standards and the possibility, that they gain broad acceptance and an according lobby. I furthermore don't believe that the manufacturers of monitors will simply let things go their own course. The free market will not permit this. The macro-environmental factors are too complex. The development heavily depends on whether a major manufacturer exterminating the others will get established or a technology will be developed at great expense that generate added value. Manufacturers which don't contribute to the glasses' development will make every effort to impede them from succeeding. It doesn't depend on whether or not people want this, but on whether this will be enforced.

What risks have to be addressed in particular (e.g. functional risk, economic risk, social risk, IT security risk, etc.)?

I can see a financial risk in terms of a corporate risk. I would approve such standards, which were for example developed at Fraunhofer Institute and which then would be offered to other companies and thus could slip the new techniques in. This would be certainly helpful; better than if a concern would obtain exclusive rights to it and then would attempt to get started on market as a standalone player.

What risks have to be addressed from a consumer perspective?

Undoubtedly, data privacy and IT security play a role; but this is a more global theme. My answer above referred to the hardware, not to the software. If there would be a complex operating system and it would be spurred and certain data could be derived by sensors and these data would be provided for economy, then this would pose a risk to the protection of personal data. But this risk is not inherent to wearable technologies. In other words: the problem doesn't start with wearables, but with data security. For instance: the operating system Microsoft – this is literally a spy in the house. We should try to maintain our data protection and security standards and not to focus on what could happen; because you can intercept this in the case of wearables. In the case of things that proceed in the background, for example fingerprint, it becomes much more complicated. In sum, I don't think that the end user is more jeopardised than usual. The risk must be differentiated according to a hardware and a software perspective. Nevertheless, I would not exclude it that wearables might fuel the possibility of eavesdropping sensitive data. However, I do not want to indicate this: the main point is that we have new technologies.

In your opinion, what changes of behavioural habits are likely to occur? How do you assess the importance of the wearable computing phenomenon for society?

The society will have to deal with the fact that you have your high-performance electronics always with you and that you can make full use of it. This will lead to a division of society, as there are on the one hand those who can

use it as they can afford it and on the other hand those who can't use it because of financial and other aspects. For instance, people with and those without an iPhone; some just can't afford them. As a result, the society already diverges heavily what poses also a risk. The society will definitely change and become more reliantly. By means of wearables people will begin to live increasingly with digital data. The living comfort will be put upward pressure. One can already see smartphones everywhere, in every tram, in every bus. And in the case of wearables it becomes even easier to take a quick look and also to access information ubiquitously, permanently. You can see who have called you, all appointments, the heart rate, and such things. People will increasingly start to network.

First of all, thank you for your information! Would you like to discuss any further topic-related issues outside the matters raised so far?

One ends up wondering how this will be implemented as a whole and how to live and to cope with it. Only because all is possible it doesn't mean that you must do all. If this were to be the case than you have to take advantage of it – or can you skip a thing in advance due to data privacy or ethical or other reasons? We have manufacturers of the new virtual reality glasses where FSK approval only be obtained from 10 years onwards. I think this is rightly. You have no experience yet regarding to those who grew up with these technologies and who are just technophile. It is also not yet known what will happen later in the market. You have to look forward to this. But particularly in the private sector it is exciting in any case how all this will develop.

A.4) Interview Transcript 3

We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you as a professional? And what role do wearable technologies play in your company? What technologies are utilized for what purposes?

As a lecturer at the University of Applied Sciences I work together with my students on a peer-coaching solution within the scope of a selective course. The aim is to employ smartwatches quasi in terms of a playground in order to assess their potential and added value. In the course of our project the employment agency represents an important stakeholder for us. In this context, the bring-your-own-device trend can be seen as a starting point for the use of wearables at workplace. Analogous to smartphones wearables will first disseminate in the mass market and then, consequently, will be brought to the workplace. There are many security aspects to resolve here. In addition, I’m supervising projects in the fields of emotion recognition, reflective learning, mobile learning assistance, thus in the context of e-learning.

What is your assessment regarding the current development of the wearable technology market? What market potential do you see?

With regard to smartwatches the developments in end consumer markets continue to look uncertain, as their added value isn’t clearly visible. They also lack technological maturity. For instance, the battery problems have to be resolved, yet. In addition, wearables are still higher-priced products and are thus rather perceived as prestige objects. With regard to smart glasses acceptance at mass market will continue lacking even in the intermediate-term; definitely not in five years. The technology is simply not mature yet. Furthermore, aesthetical and functional aspects have to be addressed, for example the form of the spectacle frame – in the end they ought to fit different face shapes. It becomes clear therefrom that the whole value chain is affected and thus has to be newly defined, for instance with regard to new alliances with eyewear manufacturers. Ultimately, diffusion of wearables will proceed successively in spite of initial acceptance problems, what is best exemplified by Google’s Street View: initially, there have been massive privacy concerns what have changed little by little. Another example would be the CCTV.

From a usability perspective, the dissemination of wearables on consumer markets is inevitable, whereby glasses have the most potential, provided that they feature technological maturity. To allege an example here, the iPhone can be mentioned that marks a breakthrough innovation because of its intuitive handling.

What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?

Most likely technological factors will therefore contribute to the dissemination, see battery runtime or the necessity of optimising the input modalities. However, eventually the social aspect is more important. The social dynamic represents currently an ‘anti-dynamic’. This trend must be reverted. It is decisive here – again with regard to smartphones – that wearables will be perceived as ‘awesome’. Hence it is important how the social environment responds.

How did your students respond to the smartwatches?

My students think that smartwatches are very cool, but actually only a few students use wearables. The real issue at stake here is how far smartwatches are useful as interface of the mobile phone - the added value continues lacking. For technically oriented students wearables represent rather a technical gimmick.

What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?

In the industry, within the working environment in the years ahead particularly smart glasses will be on the rise primarily due to their property that they allow for a seamless integration into the everyday life and provide all relevant information without the need of explicitly accessing the information ambidextrously. That is, you can handle them hands-free. I can imagine that in the private environment the application scenario 'cooking' would be very useful; but also 'Ikea instructions', which you can retrieve during the installation hands-free. With regard to smart clothes there will be especially in the health area decisive changes. In particular, the point of continuous monitoring will change the healthcare world in the long term. Internet doctors represent a viable application, as well. However, at the moment such scenarios are still in an early prototype stage. Overall, smart clothes will open completely new communication possibilities.

What in your opinion are the main incentives for integrating such technologies in everyday life? Please sort the following topics by relevance ranking:

- **i. Boost of personal abilities,**
- **ii. Improvement of health and fitness,**
- **iii. Boost of self-confidence,**
- **iv. Helps feel more in control of personal life,**
- **v. Enhancement of social relationships.**

In professional environments I would assume the following prioritisation: i. (here it is of particular importance to be proactively informed, to access information easily), iii., iv., v., ii.

In a private environment, especially with regard to smartwatches, I would assume the following: ii., iv., iii., i., v.

What do you expect from wearable computing solutions? What functionalities are of major significance, e.g. certain sensory features or context-awareness?

You have your wearable always with you, so that processes become more targeted, for example by means of Location Based Services. This implies huge time savings, as both hands are free. In logistics, for example in the building industry, there is a great need for such devices. Of course, on the hardware side it must be adequate, for example with regard to the battery management. Ultimately, however, it is also a question of acceptance; one should learn from the iPhone diffusion. One should take away the fears to use wearables for the first time. Adopters will only be ready to accept this new technology if it is opportune for them. For instance, the fear of total surveillance should be compensated by the benefit that one can communicate with colleagues in the course of monotonous tasks. The focus here is on process acceleration. It is the constant availability, but also the prestige. Here we are again on the subject of Bring Your Own Device. In particular soft factors, that is motivational and affective aspects, play a vital role; thus, deliver an advantage.

What risks have to be addressed in particular (e.g. functional risk, economic risk, social risk, IT security risk, etc.)?

In legal terms, particularly smart glasses will pose surveillance concerns. It may come to no-go areas, what would pose a social dimension, as well. In functional terms for instance face recognition implies a security risk. Smartwatches to be understood as an interface rather than a standalone device do not have a disruptive effect and thus do not harbour additional risks. On the contrary, smart glasses are riskier; you can make much more things persistent, all becomes more traceable. For instance, in a Dictaphone scenario: in traditional conferences there are no protocols off the record involved. You don't know which data is critical in retrospect.

In your opinion, what changes of behavioural habits are likely to occur? How do you assess the importance of the wearable computing phenomenon for society?

The ubiquitous connectedness will increase, while on can deliberately disable the online status, of course. The change will be rather a slow process. At the beginning not much will change. In respect of smart clothes completely new communication channels may emerge, for instance how we can show emotions. This opens up entirely new dimensions of communication. It means that there will be a new way of measuring emotions and, moreover, to share emotions. In a business context capturing of emotions is more accepted to some extent in the meantime. Increasingly important topics are the consciousness-raising of emotions, reflection and reflective learning, for example in the field of fitness and health. Wearables will certainly have a supra-individual ramification, particularly in respect of the relation to the topic measurement. A target/performance comparison will be possible that affects at behavioural level.

A.5) Interview Transcript 4

We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you as a professional? And what role do wearable technologies play in your company?

We currently work on a research project in the area of wind energy. Wearable technologies are used for maintenance works. An attempt is being made to support this with wearables. Accordingly, we have contacts to several manufacturers of hardware. In our company it is a matter of smart glasses which can be employed to process data as well as for devaluation and deactivation activities. The aim is to transfer these benefits into other areas and ultimately into the consumer market.

What is your assessment regarding the current development of the wearable technology market? What market potential do you see?

It’s very promising. We have an older generation of glasses, i.e. the Epson glasses. But nowadays there is a new generation of glasses; the new Epson glasses are considerable more powerful. The quality is very good in the meanwhile and thus I also think that wearables will establish themselves on the market. We are going to work a lot with image recognition, wherefore technological maturity is of great importance.

What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?

The technical requirements must be met, so that the system works and can be employed properly, but occupational safety is also very important. For example, in the area of wind energy one has to record where to go next and, furthermore, have to wear the glasses under the helmet and a suitable handling must be available. That is, the glasses should remain on the nose and, at the same time, the reliability of the system must be given as well. Otherwise one gets no acceptance, but this is a rather technical aspect. The customers will surely also play a role, but this is yet not a topic in our company. Yet, wearables have become affordable, indeed.

What insights did you gain about wearables in respect of customer relevance and productive use?

With our project we have not quite reached that point yet, that is the product isn’t finished yet. However, there is a great interest in applying them. We're already getting huge resonance by now. There was a tremendous feedback from companies which collaborate with us, particularly with regard to the features.

What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?

At the moment I am focussing primarily on smart glasses, but once we had talked about a magnet that can be mounted on arms. Through muscle contractions hand gestures can be interpreted and this could be linked to another wearable technology. The market is there, indeed, but I can’t reduce it to a single technology. For smart glasses there is definitely a great interest, but at the moment I cannot give further details concerning the other technologies.

What in your opinion are the main incentives for integrating such technologies in everyday life?

What I find is important is the whole fitness thing, but data security aspects play a great role there. Most important are abilities, the topic learning is particularly an issue in the industry. For example, that one can capture expert knowledge by wearable technologies and make this knowledge available to new employees, for instance in the form of videos or animations.

What do you expect from wearable computing solutions? What functionalities are of major significance, e.g. certain sensory features or context-awareness?

Important is that the technical parameters will be adjust onto the same level to achieve a qualitatively well-designed technology. For example, in regard of the glasses: if you wear them half an hour, you tend in a headache direction. In addition, the image resolution isn't good enough yet.

What risks have to be addressed in particular (e.g. functional risk, economic risk, social risk, IT security risk, etc.)?

For example, smart glasses might harbour risks due to their transparency, as they can distract. For private persons it could be extremely dangerous in road traffic or in a working environment where you must stand on a ladder. You have to mind that people don't run into danger in terms of physical risks.

In your opinion, what changes of behavioural habits are likely to occur? How do you assess the importance of the wearable computing phenomenon for society?

Things could not be worse with regard to smartphones. It depends on how intelligent the system really is, whether the system proactively indicates certain things or just reacts to the user. However, if you think of a fitness app: you use wearables only if you actually need them, for example when doing sports.

A.6) Interview Transcript 5

We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you as a professional? And what role do wearable technologies play in your company?

I work as a senior system administrator in a data processing company. I use the Pebble smartwatch primarily as a notification tool, since we receive a lot of crucial customer requests upon which we should react as soon as possible. I’m not always sitting at my desk, so the watch notifies me directly about incoming mails and I can also read them directly on the watch. The watch, which I’m bringing in privately, represents an interface to my business mobile phone. Several of my colleagues handle things the same way.

What is your assessment regarding the current development of the wearable technology market? What market potential do you see?

It is a booming market that increasingly expands into other fields. For example, in the toy sector or in the field of fashion wearable technologies are becoming more and more integrated.

What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?

First of all, the technology must be mature. Once a certain number of technically-oriented adopters will be achieved, wearables will progressively enter ordinary households.

What insights did you gain about wearables in respect of customer relevance and productive use?

They are practical. Furthermore, wearing them opens the possibility to enter discussions with customers and to arouse their interest regarding smartwatches and even to sell some.

What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?

Smartwatches and fitness trackers have already succeeded and will continue to be successful, followed by smart glasses in the middle-term.

What in your opinion are the main incentives for integrating such technologies in everyday life? Please sort the following topics by relevance ranking:

- **i. Boost of personal abilities,**
- **ii. Improvement of health and fitness,**
- **iii. Boost of self-confidence,**
- **iv. Helps feel more in control of personal life,**
- **v. Enhancement of social relationships.**

iv., i., ii., iii., v., whereby one must mention that some colleagues are using their smartwatch to check e-mails of their friends in a timely manner.

What do you expect from wearable computing solutions? What functionalities are of major significance, e.g. certain sensory features or context-awareness?

Informing of messages and reminders are most important to me at the moment. Basically, functions for monitoring the physiological condition are very useful, too.

What risks have to be addressed in particular (e.g. functional risk, economic risk, social risk, IT security risk, etc.)?

Data security is very important, as wearables capture and store sensitive personal data that is highly worth protecting. For example, to take advantage of wearables in many cases having access to cloud computing technologies is compulsory, so that all data are stored at the provider's end. In the end, usage of such services depends on the perceived trustworthiness of the cloud computing technologies.

In your opinion, what changes of behavioural habits are likely to occur? How do you assess the importance of the wearable computing phenomenon for society?

The urge for self-tracking will widely increase and the use of social media will perhaps be even more compulsive.

A.7) Interview Transcript 6

We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you as a professional?

I use wearables – in particular with regard to my smartwatch – as an interface to my smart phone in order to support my work by means of notifications.

What is your assessment regarding the current development of the wearable technology market? What market potential do you see?

Overall, there is clearly an upward trend visible, especially in respect of wristwatches and wristbands.

What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?

I think technological, economic and social aspects; in that order.

What insights did you gain about wearables in respect of customer relevance and productive use?

Wearables provide relevant information in real-time and, what is more, they provide the information proactively.

What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?

I think smartwatches and fitness bands will continue to propel this trend; at least in the near future.

What in your opinion are the main incentives for integrating such technologies in everyday life? Please sort the following topics by relevance ranking:

- **i. Boost of personal abilities,**
- **ii. Improvement of health and fitness,**
- **iii. Boost of self-confidence,**
- **iv. Helps feel more in control of personal life,**
- **v. Enhancement of social relationships.**

In particular the enhancement of performance efficiency is at the forefront. Apart from that I think that the improvement of health is very important.

What do you expect from wearable computing solutions? What functionalities are of major significance, e.g. certain sensory features or context-awareness?

I would expect a seamless integration of information services into everyday life. Thereby, both the work processes and decision-making should be supported.

What risks have to be addressed in particular (e.g. functional risk, economic risk, social risk, IT security risk, etc.)?

Apart from the current acceptance problem […] early adopters are particularly capable of suffering. However, in the end one opens up the Pandora's Box. You don't know how all will develop with respect to the constant monitoring. For example, insurance carrier could calculate their risk models according to the captured data, what to my knowledge is the case for at least one health insurance.

In your opinion, what changes of behavioural habits are likely to occur? How do you assess the importance of the wearable computing phenomenon for society?

By means of the increasing surveillance that is caused not only by wearables, but represents a more general phenomenon, we change our behavioural habits. Ultimately, this represents a restriction on personal rights in a hitherto unknown extent. This will certainly also prove for wearables, that is, wearable technologies will contribute additionally to the mass surveillance. This really verges almost on a deprivation of liberty from my viewpoint.

A.8) Interview Transcript 7

We are interested in the development of the future market „Wearable Technology“. In our context the term “Wearable Computing” is to be understood as the constant application of portable, continuously running computer systems, e.g. smartwatches or smart glasses. From your point of view, what role do wearable technologies play for you as a professional? And what role do wearable technologies play in your company?

First and foremost, I think of smartwatches when confronted with the term “wearable computing”. Personally, I don’t employ wearable technologies. However, in the course of my research semester at a research and development department of Google Zurich smart glasses were used by several employees for the purpose of pilot studies.

What is your assessment regarding the current development of the wearable technology market? What market potential do you see?

Wearables are yet in an early stage of diffusion. In the long term they will certainly proliferate massively. At the moment they are primarily adopted by early adopters what is commonly the case for technology-based innovations.

What factors (e.g. technological, economic or social) contribute most to the dissemination of wearables on consumer markets?

The most important factor is surely the economical one; that is, how the pricing system develops in the course of time. In addition, general technical conditions always play a crucial role. In this context I can further on come up with the topic of data privacy, especially when I’m thinking of Google Glasses. Here, political parameters will likely have a significant impact on their dissemination. Nevertheless, eventually the user will certainly determine the success of wearables.

What insights did you gain about wearables in respect of customer relevance and productive use?

As the glasses had been worn only for testing purposes during my stay there at Google Zurich, I can’t say anything on this.

What in your opinion are the main incentives for integrating such technologies in everyday life? Please sort the following topics by relevance ranking:

- **i. Boost of personal abilities,**
- **ii. Improvement of health and fitness,**
- **iii. Boost of self-confidence,**
- **iv. Helps feel more in control of personal life,**
- **v. Enhancement of social relationships.**

I would put it like this: i., ii., iv., iii., v.

What kind of wearables will become most important for stakeholders in the coming years, e.g. smartwatches, smart glasses, smart clothes?

I think that particularly activity trackers and other sport accessories will continue to gain popularity. With regard to various criteria such as battery power I would expect that smart glasses supposedly will take a long time to diffuse in the mass market.

What do you expect from wearable computing solutions? What functionalities are of major significance, e.g. certain sensory features or context-awareness?

You don't have to input data explicitly; the sensors automatically capture all relevant information. In particular I think of efficiency improvements in work processes.

What risks have to be addressed in particular (e.g. functional risk, economic risk, social risk, IT security risk, etc.)?

Especially data privacy is here, undoubtedly, of uttermost importance. Information may be disclosed elsewhere then originally intended by the users or contingently be tapped or eavesdropped by third parties. One has thus to trust that this won't happen.

In your opinion, what changes of behavioural habits are likely to occur? How do you assess the importance of the wearable computing phenomenon for society?

In the short term there won't be big changes. However, in the long term the consequences of the wearable computing phenomenon for society are not foreseeable. In any case, wearable computing will foster an always-on culture.

First of all, thank you for your information! Would you like to discuss any further topic-related issues outside the matters raised so far?

I think that wearables – in particular with regard to health-related data – will play an important role in future. For me as a lecturer it would also be an interesting possibility if I could just read off the names of my students from my smart glass.

A.9) Content Analysis Results Matrix

Category	Constructed Code	Sum	Number Interviews	I1	I2	I3	I4	I5	I6	I7
Acceptance behaviour	Acceptance	9	4		2	5	1		1	
	Socio-psychographic factors of adoption	11	5		1	6	1		2	1
Innovativeness	Level of innovativeness	2	1		2					
	Fear of innovations	2	2			1			1	
	Early Adopter	3	3			1			1	1
IT security aspects	IT security	4	4	1	1	1				1
	System reliability	1	1				1			
	Third Party Access	2	1							2
	Sensitive personal data	4	3	2		1		1		
	Surveillance	5	3	1		2			2	
	Privacy	11	7	1	4	1	1	1	1	2
Macro-environment	Technical immaturity	21	7	1	5	5	4	1	3	2
	Price as an economical factor	10	6	1	4	1	1		2	1
	Competitive factors	3	1		3					
	Political and legal aspects	4	3			2	1			1
Perceived Risk	Physical risks	1	1				1			
	Generally risky	1	1			1				
Perceived Usefulness	Relative Advantage	12	5	4	1	5	1			1
	Control of networked devices	2	1	2						
	Work support	24	7	8	1	2	4	3	5	1
	Health	17	5	4		5	2		1	5
	Quantified Self	10	4	2	2	5		1		
	Safety	1	1	1						
	Efficiency enhancement	7	4	1		2			3	1
	Learning aid	25	5	5		9	3	3		5
	Error reduction	3	3	1			1		1	
	Entertainment	3	2	2		1				
	Strengthens social relationships	11	4	5	1	2		3		
	Enhancement of self-confidence	5	3	1		2				2
	Gamification	1	1	1						
	More comfort of life	1	1		1					
	Schedule control	5	3		1	2				2
	Many application scenarios	2	2				1	1		
	Boosts fitness	7	5	1		1	2	2		1
	Continuous and persistent logging	4	3	1	1	2				
	More transparency and traceability	1	1			1				
	Ubiquitous connectivity	2	2			1		1		
Personality	Curiosity	2	2		1	1				
	Lifestyle	1	1		1					
	Status-Consciousness	4	3		1	2	1			
	Intrinsic motivation	3	3	1		1		1		
	Open to new ideas and experiences	2	2			1			1	
	Involvement	7	4		1	2	2	2		
Pervasiveness	Context-awareness	5	3	2		1				2
	Sensory features (multimodality)	11	5	1	1	7	1			1
	Proactive	7	6	1		2	1	1	1	1

	Convenient	9	4	4	2			2		1
	Handsfree working	8	3	3		4				1
	Information accessibility	9	6	3	1	1	1	2	1	
	Seamless integration into everyday life	5	3	3		1			1	
	Real-time operation and output	5	3	2				2	1	
	Always on	6	5		1	2	1	1		1
	Non-distracting	2	2			1	1			
	Ubiquitous	1	1		1					
Prior Experience	Familiarization with wearables	3	3	1	1		1			
	Prior Experience	3	3			1		1	1	
	No personal experience	1	1							1
Social Influence	Other-directedness, Imitation	2	2		1			1		
	Reactions of the social environment	1	1			1				
Trust	Trust in consequences of usage	4	3		1				2	1
	Trust in the system's functionality	2	2		1		1			
Usability	Fashionability and wearing comfort	6	5	1	2	1	1	1		
	High demands on effectiveness and efficiency	6	3		1	1	4			
	Demands on the range of functions	1	1				1			
	Usability	5	3		2	1	2			
Behavioural change	Behaviour modification due to continuous monitoring	2	1						2	
	Mergence of private and business life (BYOD)	3	2	1		2				
	Lives become more "digitized"	2	2		1			1		

B.1) Online Questionnaire

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Dear participant,

The purpose of this online survey is to analyse acceptance determinants of wearable computing. Your responses will be combined with those of others to help increase the understanding of the success factors of consumer's acceptance of wearables. This is a research project being conducted by Lena Gribel at Plymouth University.

Your participation in this research study is voluntary. If you decide to participate in this research survey, you may withdraw at any time. The procedure involves filling an online survey that will take approximately 8 – 10 minutes. There are no right or wrong answers, so please choose the survey responses that best describe your own opinion. Your responses will be kept confidential and identifying information such as your name, email address or IP address won't be collected. Since all responses will remain anonymous, they can no longer be erased after exiting the study. The results of this study will be used for scholarly purposes only.

If you have any questions about the research study, or face any technical problems, please feel free to contact me personally at: lena.gribel@plymouth.ac.uk.

Many thanks for your participation!

Electronic Consent

Clicking on the "agree" button below indicates that:

- You have read the above information
- You voluntarily agree to participate

If you do not wish to participate in the research study, please decline participation by clicking on the "disagree" button.

- (•) agree
- ( ) disagree

Next

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Wearables – The technologies of the future

Wearables are computer systems, which are worn on the body. They are supposed to support every day activities, e.g. through supplementary information or instructions. Wearables are characterised by an advanced sensor technology, continuous data processing, and active user support.

Examples include **smart watches** and **smart glasses**. These devices collect and analyse the relevant information (e.g. body and location data) and, if necessary, transfer the data to a smartphone or PC for further processing. Especially smart glasses provide augmented reality applications, where captured images from the outside world are supplemented by additional information.

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11% completed

1. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.

Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

Wearables are...

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
fascinating	○	○	○	○	○	○	○
boring	○	○	○	○	○	○	○
exciting	○	○	○	○	○	○	○
appealing	○	○	○	○	○	○	○

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2. Please indicate which of the following statements does apply to you.

- I regularly use wearables
- I occasionally use wearables
- I have heard about wearables before
- I have not heard about wearables before

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22% completed

3. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = "does not apply" to 7 = "fully applies".

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
Wearables boost my personal abilities.	○	○	○	○	○	○	○
Wearables improve my health and fitness.	○	○	○	○	○	○	○
Wearables boost my self-confidence.	○	○	○	○	○	○	○
Wearables help me feeling more in control of my life.	○	○	○	○	○	○	○
Wearables enhance my social relationships.	○	○	○	○	○	○	○

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28% completed

4. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
Wearables will be trustworthy	○	○	○	○	○	○	○
I will not need to be cautious with wearables	○	○	○	○	○	○	○
I think wearables will work well	○	○	○	○	○	○	○

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33% completed

5. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
The wearable is available to use wherever I need it	○	○	○	○	○	○	○
The wearable is available to use whenever I need it	○	○	○	○	○	○	○
I am able to use the wearable anytime	○	○	○	○	○	○	○
The wearable is accessible everywhere	○	○	○	○	○	○	○
The wearable is always available to me	○	○	○	○	○	○	○

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39% completed

6. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.

Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
My attention does not need to be focused on the wearable the whole time	○	○	○	○	○	○	○
I don’t have to concentrate fully on the wearable when using it	○	○	○	○	○	○	○
The usage of the wearable does not disrupt me from other activities	○	○	○	○	○	○	○
The wearable does not distract me too often	○	○	○	○	○	○	○
The wearable does not require continuous attention	○	○	○	○	○	○	○

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44% completed

7. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.

Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
Wearables are able to adapt to changing conditions (e.g. show track and heart rate during sports)	○	○	○	○	○	○	○
Wearables automatically adapt to the situation at hand	○	○	○	○	○	○	○
Wearables can automatically trigger actions relevant to the situation (e.g. in the case of smartwatches displaying the time when turning the wrist)	○	○	○	○	○	○	○

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50% completed

8. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

I think...	does not apply **1**	**2**	**3**	partially applies **4**	**5**	**6**	fully applies **7**
I could not use the wearable due to hardware failure (e.g. defective sensors)	○	○	○	○	○	○	○
I could not use the wearable due to network failure	○	○	○	○	○	○	○
I could not use the wearable due to software failure (e.g. crashing apps)	○	○	○	○	○	○	○

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56% completed

9. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply **1**	**2**	**3**	partially applies **4**	**5**	**6**	fully applies **7**
My data could be processed or transmitted incorrectly by the wearable	○	○	○	○	○	○	○
The recorded data could be altered	○	○	○	○	○	○	○
The recorded information could be incorrect	○	○	○	○	○	○	○

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61% completed

10. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
I would feel my recorded data would not be secure from unauthorised use	○	○	○	○	○	○	○
My recorded data could be used fraudulently by third parties	○	○	○	○	○	○	○
Others could easily read confidential data recorded by my wearable	○	○	○	○	○	○	○

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67% completed

11. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
It is very likely that I will use wearables	○	○	○	○	○	○	○
I will definitely try out wearables	○	○	○	○	○	○	○
As soon as it’s possible I will use wearables	○	○	○	○	○	○	○

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72% completed

12. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = "does not apply" to 7 = "fully applies".

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
If I heard about a new information technology, I would look for ways to experiment with it	○	○	○	○	○	○	○
Among my peers, I am usually the first to try out new information technologies	○	○	○	○	○	○	○
I like to experiment with new information technologies	○	○	○	○	○	○	○

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78% completed

13. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.
Please evaluate with 1 = "does not apply" to 7 = "fully applies".

I see myself as someone who ...	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
... is reserved	○	○	○	○	○	○	○
... is generally trusting	○	○	○	○	○	○	○
... tends to be lazy	○	○	○	○	○	○	○
... is relaxed, handles stress well	○	○	○	○	○	○	○
... has few artistic interests	○	○	○	○	○	○	○
... is outgoing, sociable	○	○	○	○	○	○	○
... tends to find fault with others	○	○	○	○	○	○	○
... does a thorough job	○	○	○	○	○	○	○
... gets nervous easily	○	○	○	○	○	○	○
... has an active imagination	○	○	○	○	○	○	○

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83% completed

14. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.

Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
Simply knowing the answer rather than understanding the reasons for the answer to a problem is fine with me.	○	○	○	○	○	○	○
I prefer my life to be filled with puzzles that I solve.	○	○	○	○	○	○	○
I would prefer complex to simple problems.	○	○	○	○	○	○	○

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89% completed

15. For each of the subsequent listed statements please indicate to which extent they do apply or do not apply to you.

Please evaluate with 1 = “does not apply” to 7 = “fully applies”.

	does not apply 1	2	3	partially applies 4	5	6	fully applies 7
I have all the things I really need to enjoy life	○	○	○	○	○	○	○
My life would be better if I owned certain things	○	○	○	○	○	○	○
I wouldn’t be any happier if I owned nicer things	○	○	○	○	○	○	○
I’d be happier if I could afford to buy more	○	○	○	○	○	○	○
It sometimes bothers me that I can’t afford to buy all the things I’d like.	○	○	○	○	○	○	○

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94% completed

I am... female

16. Please choose your age below

20 to 29 years

17. Which is your highest level of educational attainment?

- ○ no school-leaving qualification
- ○ secondary modern school qualification
- ○ secondary school certificate
- ◉ completed apprenticeship
- ○ A level
- ○ university degree
- ○ other

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B.2) Cross-loadings

	Agreeablenes s	Behavioural Intent to Use Wearables	Conscientiousness	Extraversion	IT Security Risks	Involvement	Need for Cognition	Need for Materialism	Neuroticism	Openness to Experience	Perceived Pervasiveness	Perceived Usefulness	Trust
AZ03_01	-0,031	1,000	0,017	0,204	-0,388	0,715	0,280	0,292	-0,064	0,132	0,631	0,782	0,673
IV01_02	0,086	0,494	0,090	0,191	-0,184	0,843	0,097	0,133	-0,010	0,111	0,562	0,570	0,529
IV01_04	0,013	0,730	-0,008	0,190	-0,250	0,908	0,246	0,275	-0,011	0,131	0,616	0,758	0,647
LOC_Availability	-0,127	-0,182	-0,195	-0,113	0,558	-0,130	-0,085	0,061	0,170	0,058	-0,151	-0,121	-0,237
LOC_Confidentiality	-0,117	-0,380	-0,123	-0,114	0,946	-0,211	-0,071	-0,067	0,094	0,079	-0,197	-0,289	-0,332
LOC_Context_Awareness	0,022	0,520	-0,030	0,210	-0,190	0,598	0,198	0,191	-0,051	0,196	0,839	0,593	0,661
LOC_Integrity	-0,132	-0,303	-0,185	-0,123	0,851	-0,211	-0,087	-0,001	0,134	0,042	-0,226	-0,221	-0,327
LOC_Ubiquity	-0,018	0,546	-0,034	0,222	-0,174	0,629	0,208	0,225	-0,066	0,209	0,894	0,641	0,726
LOC_Unobtrusiveness	-0,072	0,509	0,027	0,120	-0,213	0,433	0,239	0,109	-0,149	0,112	0,756	0,499	0,524
NZ04_01	-0,021	0,730	0,059	0,230	-0,284	0,708	0,229	0,315	-0,012	0,129	0,637	0,925	0,673
NZ04_02	-0,008	0,711	0,001	0,226	-0,230	0,737	0,210	0,265	-0,005	0,138	0,662	0,927	0,683
NZ04_03	0,016	0,648	0,034	0,189	-0,278	0,602	0,232	0,305	-0,009	0,074	0,533	0,800	0,619
NZ04_04	-0,032	0,663	-0,050	0,169	-0,273	0,623	0,190	0,333	0,037	0,080	0,604	0,856	0,666
NZ04_05	-0,004	0,594	-0,005	0,169	-0,268	0,492	0,233	0,300	-0,017	0,086	0,465	0,718	0,561
NZ05_01	-0,011	0,637	0,044	0,245	-0,325	0,645	0,278	0,207	-0,070	0,133	0,734	0,726	0,928
NZ05_02	0,006	0,670	0,060	0,254	-0,349	0,651	0,249	0,249	-0,066	0,162	0,701	0,720	0,925
NZ05_03	0,018	0,562	0,060	0,217	-0,326	0,576	0,218	0,202	-0,115	0,148	0,712	0,624	0,928
PS01_01	0,070	0,168	0,355	0,847	-0,162	0,172	0,219	-0,084	-0,351	0,207	0,116	0,163	0,133
PS01_03	0,231	0,017	1,000	0,315	-0,151	0,024	0,137	-0,273	-0,403	0,098	-0,017	0,012	0,059
PS01_04	-0,089	-0,076	-0,168	-0,140	0,019	-0,006	-0,257	0,168	0,729	-0,239	-0,125	-0,035	-0,101
PS01_06	-0,029	0,184	0,200	0,882	-0,060	0,205	0,247	-0,030	-0,272	0,308	0,263	0,242	0,303
PS01_07	1,000	-0,031	0,231	0,020	-0,130	0,036	-0,096	-0,153	-0,157	-0,060	-0,028	-0,018	0,005
PS01_09	-0,158	-0,040	-0,443	-0,398	0,137	0,004	-0,176	0,269	0,904	-0,159	-0,064	0,020	-0,059
PS01_10	-0,060	0,132	0,098	0,301	0,067	0,152	0,198	0,049	-0,227	1,000	0,210	0,134	0,160
PS02_05	-0,090	0,317	-0,184	-0,023	-0,070	0,261	0,036	0,848	0,136	0,055	0,237	0,336	0,250
PS02_07	-0,107	0,320	-0,219	-0,013	-0,099	0,273	0,018	0,919	0,236	0,048	0,220	0,339	0,256
PS02_08	-0,200	0,162	-0,313	-0,124	0,017	0,150	-0,034	0,900	0,337	0,032	0,129	0,231	0,140
PS03_02	-0,093	0,260	0,158	0,289	-0,079	0,206	0,934	0,004	-0,299	0,203	0,238	0,233	0,251
PS03_04	-0,080	0,249	0,081	0,190	-0,068	0,195	0,881	0,005	-0,128	0,150	0,229	0,205	0,234
IV01_01	0,016	0,659	0,006	0,210	-0,182	0,937	0,220	0,240	0,020	0,162	0,619	0,694	0,619