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The Mood of the Silver Economy: A Data Science Analysis of the Mood States of Older Adults and the Implications on their Wellbeing

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***Abstract*—For the first time in the history of humanity, the number of people over 65 surpassed those under 5 in 2018. Undoubtedly, older people will play a significant role in the future of the economy and society in general, and technological innovation will be indispensable to support them. Thus, we were interested in learning how home automation could enable older people to live independently for longer. To better understand this, we held focus groups with UK senior citizens in 2021, and we analyzed the data derived from them from the perspective of affective computing. We have trained a machine learning classifier capable of distinguishing moods commonly associated with older adults. We have identified depression, sadness and anger as the most prominent mood states conveyed in our focus groups. Our practical insights can aid the design of strategic choices concerning the wellbeing of the ageing population.**

I. Introduction

IN THE EUROPE of 2060, one in three inhabitants will be over 65 [1]. A similar trend of increasing life expectancy and reversal of the population pyramid will be followed by the rest of the developed countries [2]. The forms of consumption will therefore change and older people will become the engine of the so-called *silver economy* [3].

The silver economy includes all the economic activities, products and services designed to meet the needs of older adults [4]. The concept derived from the *silver market* that emerged in Japan—the country with the highest percentage of people over 65—during the 1970s [5], and brings together sectors as diverse as health, banking, automotive, energy, housing, leisure and tourism. Scientific advances and joint efforts will be critical to address the unique health challenges of the ageing population and their communities [3]. Undoubtedly, the ageing of the population will lead to the creation of jobs and the emergence of careers related to the silver economy.

Regrettably, mental health problems in older adults are frequent. Indeed, late life depression is common, and it is typically associated with disability, reduced quality of life, mortality, and high health care costs [6]. Moreover, depressed older adults frequently have comorbid medical illnesses and cognitive impairments [6]. Life events such as moving from a private residence to a nursing home, or an assisted-living facility, can trigger symptoms such as anxiety, confusion, hopelessness, and loneliness. This is part of a nursing diagnosis now known as *relocation stress syndrome* [7].

In an attempt to prevent relocation stress, the *AGE IN* project endeavours to propose a strategy to keep the ageing population independent for longer in their own homes [8]. AGE IN has suggested a combination of house adaptations and the development of a local ecosystem for the silver economy [8]. As shown in recent studies [9], one of the keys to the silver economy will be technological innovation. Advances in home automation, artificial intelligence, the Internet of Things, eHealth and other services typical of smart cities, will prove relevant to support the ageing population.

To bring the AGE IN strategy to fruition, it is vital to understand the needs and concerns of older adults. Consequently, we organized a series of focus groups in the summer of 2021, where UK senior citizens participated in discussions about independent living, house adaptations, isolation, and their concerns about the future. Due to the sensitive nature of the focus groups, we undertook the ethical approval process required by the *University of Plymouth*, which is where the focus groups were held. Our ethical approval was recorded under the title "AGE IN Robot Home" through the *Plymouth Ethics Online System* (PEOS) [10]. Our approach was reinforced by a white

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paper published by the *UK Ministry of Housing, Communities and Local Government* in 2020 [11].

Transcriptions of the conversations which took place during the focus groups that we organized allowed us to gather opinions and relevant feedback. We then processed these transcriptions with the use of text mining techniques and machine-learning algorithms to extract knowledge and insights into the feelings and emotions expressed by older adults. We expect the practical insights derived from our study to aid in the decision-making of strategic choices concerning the mental health of the ageing population—especially, as a considerable amount of fear and depression were expressed by the senior citizens who participated in our focus groups.

The remainder of this paper is organized as follows. We start by summarising the related work on emotion analysis and its links to older adults in Section II. Afterwards, we describe our dataset in Section III and its processing in Section IV. Then, we present our results in Section V, and we discuss them in Section VI. Finally, we draw our conclusions in Section VII.

II. Related Work

Plenty of multidisciplinary research has demonstrated through text analysis that word use is a reliable indicator of a person's psychological state [12]. Thus, *sentiment analysis* has been amply used to analyze people's evaluations, appraisals, and attitudes towards products, services, and topics [13], [14], [15]. However, most sentiment analysis work focuses on assigning a positive or negative rating—*polarity*—to a piece of text [16], whereas we aim to recognise a range of emotional categories, which is the goal of *affective computing* [17].

Emotions are critical for the interaction of human beings, as they enable people to express their reactions to any stimulus they experience [18]. Although the idea of employing computers to recognise emotions was first introduced by Picard in 1997 [19], it is only recently when the advances in machine learning have boosted *natural language processing* (NLP) to reach human-level performance [20].

Over the past decade, we have witnessed the publication of a great deal of literature interested in identifying emotions in text. Most of this literature has adopted supervised machine learning approaches to recognise specific sets of emotions. An example of this is Chaffar and Inkpen's research, which combined emotion-annotated news headlines, fairy tales and blogs to create a suitable training set [21]. Chaffar and Inkpen claim to have achieved a much better performance with a *support vector machine* (SVM) classifier than with any other alternative. Moreover, their SVM classifier generalises well on unseen examples [21].

We were keen on testing approaches that depart from the traditional methods followed by sentiment analysis, which used lexicons and bag-of-words models. We are aware of the improvements reported by researchers who have worked with sequences of characters, without pre-processing the text that becomes the input of a *recurrent neural network* (RNN). Colnerič and Demšar [22] implemented one of such approaches and used it to classify tweets into emotional categories. Their work is particularly relevant to ours.

Following Colnerič and Demšar [22], we have also implemented our own emotion classifier, though we did not consider the models developed by Paul Ekman [23] and Robert Plutchik [24], as Colnerič and Demšar did. Instead, we concentrated on a different model for the reasons explained below.

Ekman studied facial expressions to define six universally recognisable emotions: anger, disgust, fear, joy, sadness and surprise [23]. Even though facial recognition is an area which we wish to explore in the long term, we are currently unable to apply it. Thus, Ekman's model is not suitable for our work.

Plutchik considered eight basic, pairwise, contrasting emotions: joy vs. sadness, trust vs. disgust, fear vs. anger, and surprise vs. anticipation [24]. Even though we plan to widen the range of emotions analyzed by our classifiers as our research progresses, the lack of annotated training collections complicates any attempts to implement Plutchik's model. Ultimately, we could pursue Colnerič and Demšar's approach—that is, consider each emotion as a separate category and disregard the different levels of intensities that Plutchik defined [22]. Regrettably, such a simplification would diminish the value and full extent of Plutchik's model. Additionally, we would prefer to fine-tune our implementation for a smaller number of emotions before involving a wider range.

We favored the implementation of a third emotion model, different from Ekman's and Plutchik's, as we also wanted to identify an alternative approach that is more suitable for the study of the ageing population. This led us to consider the *Profile of Mood States* (POMS) [25], which contemplates *fatigue* and *depression*—two states of mood often associated with older adults.

In the following sections, we explain how we gathered our dataset and how we implemented our classifier.

III. Dataset

We organized meetings with 17 British senior citizens who currently live in the city of Plymouth (UK). We invited them to participate in our focus groups through our professional partnership with *Plymouth Community Homes* (`https://www.plymouthcommunityhomes.co.uk/`). We refer to these older adults hereafter as *participants*, and they were separated into three groups:

- **Group 1:** Participants whose ages were 59–80 and required daily support with mobility issues—for example, a wheelchair, a prosthetic leg or a walking aid.
- **Group 2:** Participants whose ages were 66–80 and did not require support with mobility issues.
- **Group 3:** Participants whose ages were 57–63 and did not require support with mobility issues.

For a whole morning or afternoon, the participants visited the University of Plymouth on 27–29 July 2021 and had conversations with a group of academic researchers about their views on ageing, isolation, their own future, and the relevance of using technological and automation tools to keep their independence at home. Apart from the conversations, the participants had an opportunity to attend a brief presentation delivered by *Pepper*, a semi-humanoid robot [26].

Although Pepper is not a functional robot for domestic use, it is intended to enhance people's lives and facilitate relationships [26]. Pepper did help the researchers to establish rapport with the participants of the focus groups and start the conversation about technological and automation tools.

We recorded all the conversations held during the focus groups, abiding by the guidance provided by the *University of Plymouth Ethic's Committee* [10]. Later, we transcribed all the conversations using *Trint* [27], an audio transcription software. Once the conversations were converted into transcribed text, we proceeded to manually label by gender each line of the conversations, so that we could associate each line with a female or male participant, despite removing their names for ethical considerations. We were interested in identifying the gender of the participants, as we are aware of gender differences when diagnosing conditions such as depression. Indeed, we were hoping to contribute to the research aimed at determining whether elderly women are at greater risk for depression than elderly men [28], or vice versa.

To identify the main topics of conversation in the focus groups, we performed a lexical analysis of the transcribed text. We started by undertaking some pre-processing steps commonly associated with NLP:

- **Tokenisation:** The process of splitting a piece of text into its parts, called *tokens*, while disposing of certain characters, such as punctuation. Tokens are loosely referred to as "words" in this paper.
- **Stop-word removal:** The process of eliminating extremely common and semantically non-selective words. The stop-word list that we used was built by Salton and Buckley for the experimental *SMART* information retrieval system [29] and contains 571 words.
- **Lemmatization:** The process of reducing inflectional and derivational related forms of a word to a common base [30]. Although lemmatization is slower than stemming, we favored its use based on the recent results reported by Haynes *et al.* [31].

According to *term frequency–inverse document frequency* (TF-IDF) [30], the most characteristic nouns employed by the participants of the focus groups were *people*, *family*, *home*, *friend*, *technology*, *stairs* and *shopping*, which are reflective of their everyday concerns and interests. All the characteristic keywords discovered by TF-IDF are depicted in Fig. 1 using a word cloud.

IV. Methods

POMS is a psychological instrument for assessing an individual's mood state [32]. It is a standard validated psychological test formulated by McNair *et al.* [33]. It defines 65 adjectives that are rated by the individual on a five-point scale. Each adjective contributes to one of seven categories: anger, confusion, depression, fatigue, friendliness, tension and vigour. For example, an individual who uses adjectives such as *exhausted*, *worn out* or *weary* to describe her own mood would contribute to classify her state within the *fatigue* category.

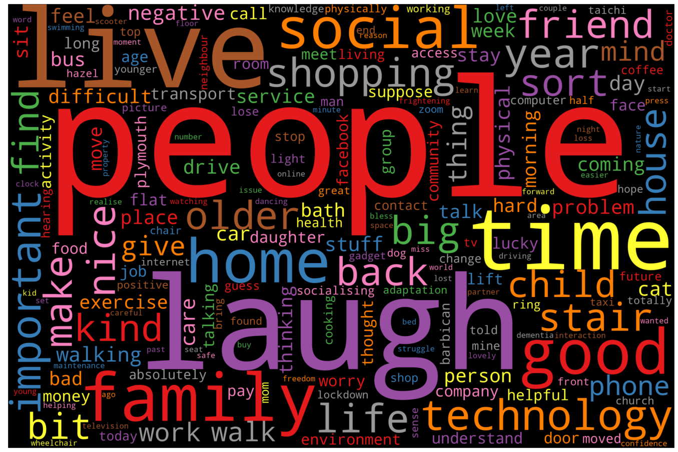

Fig. 1. Word Cloud displaying the most characteristic keywords identified by the TF-IDF weighting in the transcribed conversations of the focus groups.

POMS has been widely used to assess both medical patients and the normal population, with a large body of sports and exercise investigation based extensively on it [34], [35]. Also, instead of its intended use as an administered questionnaire, POMS has been adapted to work with large textual corpora, showing its potential benefits for measuring mood in NLP research [36], [37].

Research on loneliness has reported that fatigue—both mental and physical—is an ever-present challenge for older adults, largely owing to factors linked to loss—loss of loved ones, loss of purpose, or loss of health and vigour. For instance, Morita *et al.* [38] have studied the correlation between emotion and body movements. As an older adult's range of movement becomes limited by pain or fear of pain, confidence and specific age-related considerations—including a decline in muscle mass—contribute to a physical sense of fatigue. Thus, we were interested in a model that takes fatigue into account. This is precisely what POMS contributes.

Depression is another mood commonly associated with the ageing population. While depression, particularly late-onset depression, is not a sign of ageing, it is often perceived as such—the *Royal Society for Public Health* has found that one in four people between 18 and 34 think that being depressed in old age is normal [39]. Chronic pain, multiple medications [40], and loss and changes in lifestyle [41], all contribute to people not recognising or seeking help for depression, which can lead to untreated conditions and misdiagnoses [42].

Given that depression significantly reduces quality of life and cognitive abilities, and can be an antecedent and precursor of dementia [43], we were keen on using an emotion model that recognises depression. POMS contributed this to our work too. Based on POMS, adjectives such as *unworthy*, *miserable* or *gloomy* used to describe a person's feelings contribute to classify her state within the *depression* category [44].

We experimented with the following classifiers: SVM [45], Naïve Bayes [46], logistic regression [47], random forests

[48]—the number of trees was selected using linear search—and long short term memory (LSTM) [49].

To train the classifiers, we used Colnerič and Demšar's training set, which is based on a dataset comprising 73 billion tweets annotated using distant supervision [22]. Regrettably, the random forest was too slow; thus, we built forests with a maximum of 100 trees. Still, training 100 trees using bigrams took longer than a day on *Colab* [50]. All our work was carried out using the `scikit-learn` library [51], and all the parameters were left at their default values.

Regarding neural network architectures, we decided to use an RNN, as it can naturally handle texts of variable lengths, which would be of help when working with transcribed text. We understand that there are other architectures which may suitable, but we will have to test them in the future.

Instead of pre-processing the transcriptions, we treated each line of a conversation as a sequence of characters, and pass such characters one by one into the neural network. Then, the task of the network was to combine the characters into a suitable representation and predict the moods expressed. The neural network had to learn which sequences of characters form words, since space was not treated differently from any other character. The benefit of this character-based approach is that it does not require any pre-processing. If we were working with words, we would need a tokenizer first and then we would have to decide which morphological variations of the words are similar enough to consider them equivalent for their representation, which is what stemming and lemmatization do. However, in our character setting approach, all those decisions were left to the neural network to figure out.

Our embeddings consist of sequences of characters mapped into vectors. We used only characters that occurred in the training dataset 25 times or more, which yielded a set of 410 characters, and we removed emoticons and other symbols that were not part of our transcriptions. The embeddings were then passed through the RNN layer. We experimented exclusively with the LSTM variant, as Peng has shown that LSTM produces valuable results for text classification [52].

Although POMS comprises seven mood states, we removed the *friendliness* mood from our classifier, as Norcross *et al.* have found that the adjectives corresponding to it are too weak to ensure valid classification [25]. We also complemented the model with other adjectives derived from the *BrianMac Sports Coach* website [44]. Table I shows the full list of adjectives that we employed to identify each of the mood states.

We complemented our results with `text2emotion` [53], a well-regarded Python library to determine the emotions expressed in text. Note that `text2emotion` is based on the original work by Diaz *et al.* [18].

TABLE I
PROFILE OF MOOD STATES (POMS)—CHOSEN ADJECTIVES

Mood state	Adjectives
anger	angry, peeved, grouchy, spiteful, annoyed, resentful, bitter, ready to fight, deceived, furious, bad tempered, rebellious
confusion	forgetful, unable to concentrate, muddled, confused, bewildered, uncertain about things
depression	sorry for things done, unworthy, guilty, worthless, desperate, hopeless, helpless, lonely, terrified, discouraged, miserable, gloomy, sad, unhappy
fatigue	fatigued, exhausted, bushed, sluggish, worn out, weary, listless
tension	tense, panicky, anxious, shaky, on edge, uneasy, restless, nervous
vigour	active, energetic, full of pep, lively, vigorous, cheerful, carefree, alert

V. RESULTS

The participants of Focus Group 1 were more technologically orientated than the others. Keywords such as *Internet*, *technology* and *Zoom* were among the most characteristic keywords employed in the conversations held by the participants of this focus group. Coincidentally, the first focus group was also the one with the largest number of male participants.

Studies suggest that females feel less confident in their interaction with technology, because they have learned less and practiced less, and feel more anxious about using computers when compared with their male counterparts [54]. Nevertheless, the presence of keywords such as *Facebook*, *WhatsApp*, *computer* and *mobile* with high TF-IDF weights across the three focus groups reveals that all the participants were familiar with a variety of modern applications and items.

Generally, the focus groups conversations confirm that older adults appreciate the benefits of technology. Still, negative attitudes towards technology were expressed when referring to the inconveniences associated with it. This seems to be in line with the work of Mitzner *et al.* [55].

For illustration purposes, we have listed below a few comments extracted from the conversations that took place in the focus groups and discuss the benefits and inconveniences of interacting with technology.

- **Benefit 1:** "*I mean, I wouldn't have been able to see my family without the internet!*"
- **Benefit 2:** "*And I use it digitally for communicating with my children with a portal which is a magic machine. I just make telephone calls by saying to the television, please ring Harry and Harry's on the television.*"
- **Benefit 3:** "*So technology is good. Yeah. But then you've got to know how to use it, and also be careful, being safe as well when you're using these things. That's my priority all the time.*"
- **Inconvenience 1:** "*I tell you what makes me very sad about technology is when you hear these people, these women that get sucked in by these men for all this money. [Laughs.] It's true, isn't it? That's true. Yeah.*"
- **Inconvenience 2:** "*Doctors... now... they are a nightmare! Because I'm trying to get an E-consult and if you're not*

on the Internet now, you can't get your prescription and you can't contact doctors. That is huge!"

- **Inconvenience 3:** "*You want older people to embrace technology... make it easier. Make it less scary. Yeah, they get that. Sometimes these iPhones. I mean, I love it. I'm a geek. Yeah. As soon as there is a new technology I want it! But I've got friends that can't understand it. The technical wording is too difficult... I love it, but I don't understand a lot of it. Make it easy. We want older people or people who are scared of it to embrace the technology. Make it easy. Yeah, if that makes sense. Right?*"

Using our classifier, we assigned each line in the transcriptions a probability associated with each of the POMS categories. The values displayed in Fig. 2 represent the addition of the probabilities for each category to occur in each of the lines of the transcriptions derived from Focus Group 1.

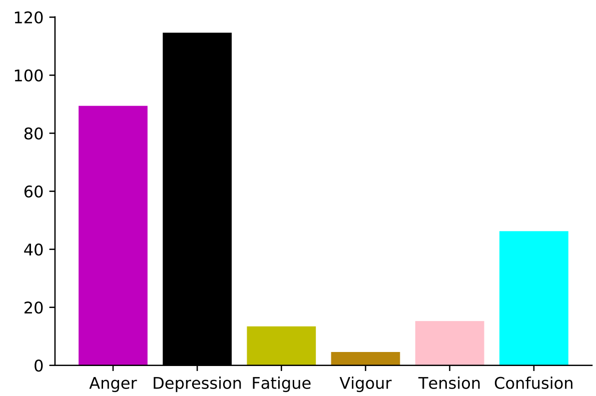

Fig. 2. Distribution of the probabilities of each of the POMS categories present in the transcriptions of Focus Group 1.

The participants in Focus Group 1 have multiple chronic health conditions and mobility impairments. In fact, some of them have already transitioned into supported-living accommodation. They have lost a degree of autonomy and are aware that their current abilities are likely to deteriorate further in the short term. Unsurprisingly, Fig. 3 shows that, according to `text2emotion`, fear is the most prominent emotion conveyed by Focus Group 1.

Beadle and De la Vega have pointed out that the decline of cognitive empathy frequently correlates with an increase in emotional empathy in older adults [56]. This may explain why the participants in Focus Group 2 engage in caring roles regularly, supporting others who are older or have additional concerns. While this provides them with a sense of fulfilment, it also increases their sadness both aimed at the recipients of their support and themselves. Fig. 4 corroborates that sadness is the most prominent emotion found in Focus Group 2.

Our POMS classifier yielded very similar results across the three focus groups. Depression, anger, and confusion are the most prominent moods in all cases. The only difference is the amount associated with each mood. Fig. 5 displays the distribution for Focus Group 2.

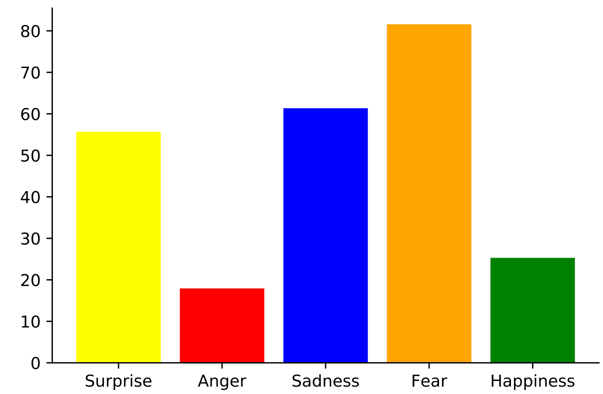

Fig. 3. Distribution of the probabilities of each of the `text2emotion` categories present in the transcriptions of Focus Group 1.

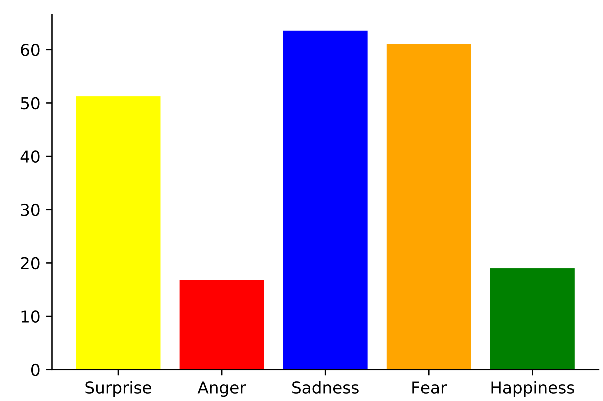

Fig. 4. Distribution of the probabilities of each of the `text2emotion` categories present in the transcriptions of Focus Group 2.

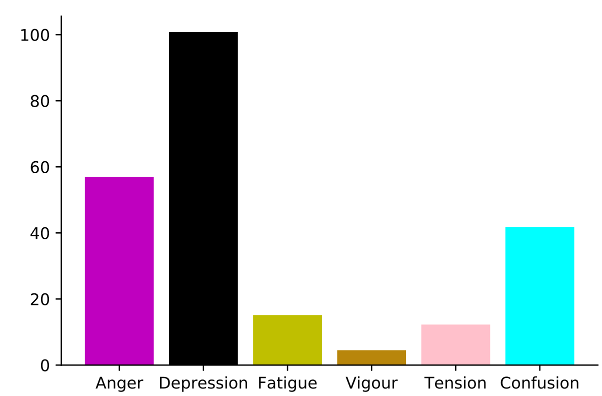

Fig. 5. Distribution of the probabilities of each of the POMS categories present in the transcriptions of Focus Group 2.

Focus Group 3 expressed a higher level of surprise than all the others, as it can be seen in Fig. 6. To explain this, it is important to examine the meaning of *surprise*. Peirce [57] and Pollard [58] define "surprise" as a reflective moment of self-realization or a new viewpoint previously unconsidered. As a younger group, with fewer health concerns, the conversations held in Focus Group 3 were mainly hypothetical or based on the participants' observations of the experiences of others.

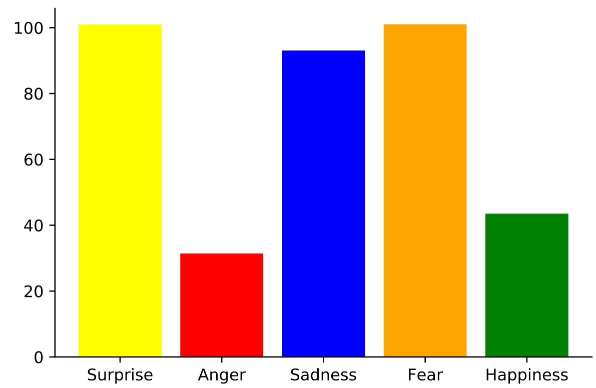

Fig. 6. Distribution of the probabilities of each of the `text2emotion` categories present in the transcriptions of Focus Group 3.

Focus Group 3 drew on examples of older adults in their families and social circles, realizing what might be to come for them. These participants were more likely to look for comparisons within the group to reflect on their own ageing process, as Sayag and Kavé have suggested [59]. Fig. 7 displays the POMS distribution for Focus Group 3.

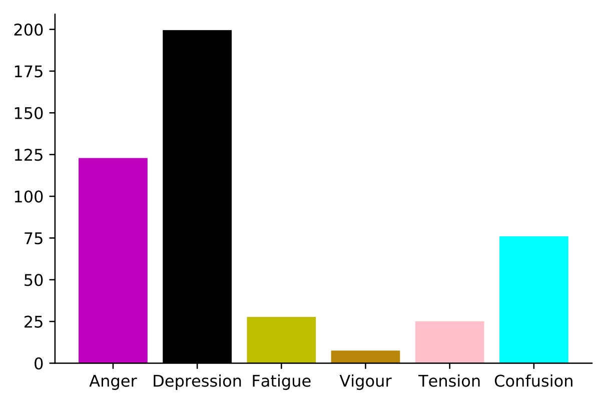

Fig. 7. Distribution of the probabilities of each of the POMS categories present in the transcriptions of Focus Group 3.

VI. Discussion

There are common themes of conversation among older adults which generate anger, depression, sadness and fear—for example, admittance into a care home [60] or susceptibility to scams [61]. However, there are also differences that can explain the variations in the mood states expressed by the participants of our focus groups. To start with, women live longer than men, on average, even when mortality is high—for instance, during severe famines and epidemics [62]. Whilst part of the gender longevity disparity can be accounted for by the nature of the work and leisure activities that a proportion of men engaged in, there is clear evidence to suggest that women live longer than men in almost all modern populations [63]. Undoubtedly, loneliness, depression, and social isolation are critical to explain why men die younger [64].

Older women have larger social networks and maintain more ties to people outside their households than older men [65]. Men who have previously relied on their partners to maintain family structures and relationships can be left without the social skills to retain and extend their connections when they lose their partners. Also, Mann [66] has explained that men's desire to demonstrate and impart their knowledge and experience can be severely impacted when they lose contacts in their late lives. As a result, men are more likely to experience depression in later life [67]. Unsurprisingly, widowed men are more prone to subsequent depression than widowed women [67]. This may be the reason why our POMS classifier detected more depression and anger from men when the analysis of Focus Group 1 was divided by gender. Fig. 8 shows the differences in moods between genders in Focus Group 1.

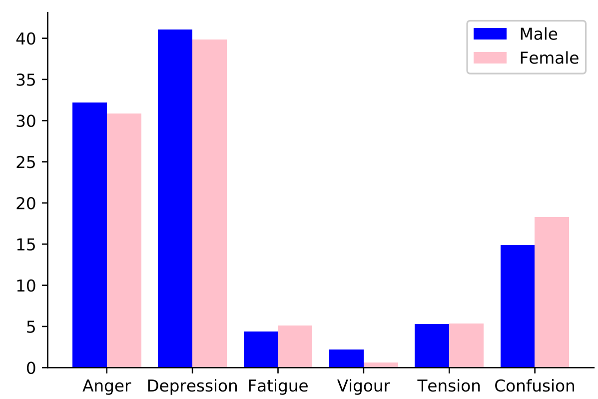

Fig. 8. Differences in moods between men and women in Focus Group 1. The histograms display the distribution of the probabilities of each of the POMS categories present in the transcriptions of Focus Group 1.

In our focus groups, men expressed more anger at falling—which is another common theme among older adults [68]—than women; whereas women identified the loss of social connections as paramount, which has also been noticed by Goll *et al.*, in a sample of older adults living independently in London, England [69].

VII. Conclusions

Words matter because our attitudes towards a subject are frequently implicit in our lexical choices. Words are reflective and expressive of our attitudes and emotions, and can also explain how we think [70], [71]. The words people use to communicate not only express what they are thinking about,

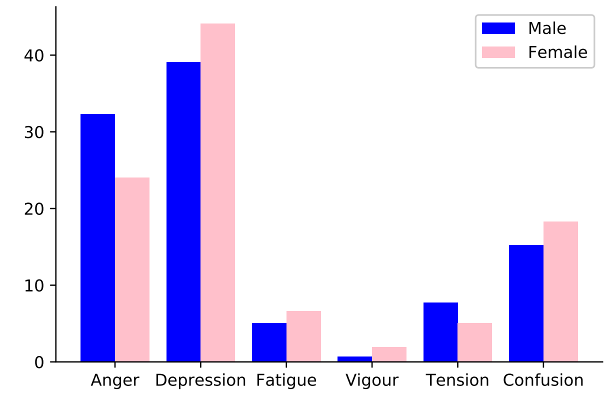

Fig. 9. Differences in moods between men and women in Focus Group 2. The histograms display the distribution of the probabilities of each of the POMS categories present in the transcriptions of Focus Group 2.

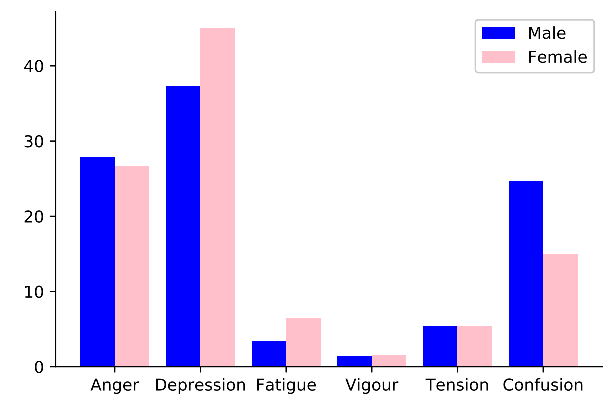

Fig. 10. Differences in moods between men and women in Focus Group 3. The histograms display the distribution of the probabilities of each of the POMS categories present in the transcriptions of Focus Group 3.

but also how they are feeling. Thus, an appropriate way to examine the attitudes of people towards an issue is to analyze the words they use to describe it, and the linguistic sentiment inherent in those words [72]. This is where the main contribution of the work presented here lies.

We have applied machine learning to analyze conversations recorded with older adults. Our analysis provides practical insights, and it can aid in the decision-making of strategic choices concerning the ageing population. The advantages of using POMS over other emotion classifiers have been discussed, and we expect to start the search for other models that are applicable for the study of older adults. This certainly helps in building a comprehensive view of senior citizens, which opens new possibilities to identify their problems and find ways to boost their wellbeing.

The *UK Office for National Statistics* has confirmed that we are living longer lives because of medical advances and safer workplaces, among other conditions [73]. Given this trend, it seems to be time to rethink how we support older adults, as well as the way in which society approaches the finances, housing, health, and care of the silver economy. Precisely, one of the current *Grand Challenge Missions* set out by the UK Government is to ensure that people can enjoy at least 5 extra healthy, independent years of life by 2035 [74]. Our current work and future developments attempt to harness the power of innovation to help meet the needs of an ageing society.

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