2021-04-25

The role of Artificial Intelligence networks in sustainable supply chain finance for food and drink industry

Olan, F

http://hdl.handle.net/10026.1/17074

10.1080/00207543.2021.1915510
International Journal of Production Research
Taylor & Francis

The role of Artificial Intelligence networks in sustainable supply chain finance for food *and drink industry*

Recto running head : INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH

Verso running head : F. OLAN ET AL.

Femi Olan[a], Shaofeng [Q1]Liu[b], Jana Suklan[c], Uchitha Jayawickrama[d], Emmanuel Arakpogun[a]

[a] Newcastle Business School, Northumbria University, Newcastle Upon Tyne, UK

[b] Plymouth Business School, University of Plymouth, Plymouth, UK

[c] NIHR Newcastle IVD Co-operative Translational and Clinical Research Institute, Newcastle University, Newcastle Upon Tyne, UK

[d] School of Business and Economics, Loughborough University, Loughborough, UK

CONTACT Femi Olan femiolan@outlook.com

History : received : 2020-07-13 accepted : 2021-04-02

ABSTRACT

In the last decade, food and drink supply chain management has become an important part of global operations strategy. The global food and drink industries (FDIs) is establishing supply chain operations across countries as a result of increasing demand, this expansion has created challenges in coordinating operations that connect multi-suppliers, one as such is the financial enabler for the multi-layered supply chain network. However, literature on artificial intelligence (AI) in FDIs is limited, this study explores AI theory in supply chain networks and alternative supply chain financing for the FDIs. This study proposes a new conceptual framework based on theoretical contributions identified through literature, a conceptual framework is established and further developed to a meta-framework. This study explored the set-theoretic comparative approach for data analysis, the outcomes of this research suggest that the probable contributions of supply chain networks driven by AI technologies provide a sustainable financing stream for the food and drink supply chain.

KEYWORDS

- Artificial intelligence
- food and drink industries
- supply chain finance
- sustainability
- supply networks

1. Introduction

The food and drink industries (FDIs) have been facing immense cash flow challenges that are affecting operations; as a result, firms are finding difficulties in sourcing funds to meet customer and supplier demands (Yakovleva, Sarkis, and Sloan 2012). In this environment, supply chain finance has become the focal point of business financing, especially since the last recession where financial services support for global supply chain industries and operations has been reduced or withdrawn (Lekkakos and Serrano 2016). Therefore, we explore the important impact of Artificial Intelligence (AI) in stimulating financial services for FDIs through supply chain network activities.

One of the impact of the economic collapse is shortage of liquidity for the FDIs (Huang, Yang, and Tu 2019). During this challenging periods, FDIs initiated the trade credit system as an alternative form of financing enabling suppliers to continue doing business, consequently leading to eventually worse situation in the supply chain (upstream) (Huang, Fan, and Wang 2019). The consequences of this financial crisis contributed to the impulse for innovative solutions that support and optimise cash flow. Among these solutions, supply chain finance (SCF) is one of the significant strategies, with the aim to ensure sustainable financial flows within the industry by implementing technologically advanced solutions such as AI.

Although there is a consensus on the impact of the financial crisis in supply chain (SC) leading to the initiative of supply chain finance. Thus, literature identify two views on the SCF: the first view is referred to as the 'supply chain-oriented' SCF, encirclements operational financial capital decisions described in its components such as cash flow and accounts payables. In addition, this perspective focuses on the optimisation of operational financial flows for FDIs (Yu, Huang, and Guo 2020). The second view, SCF focuses primarily on the 'financial view' which includes financial products for FDIs (Huang, Fan, and Wang 2019). Frequently, the financial view targets mainly 'reverse factoring' which is known as a financial agreement by which a financial institution procures accounts receivables from selected, information-transparent, high quality buyers, with a credit risk which is lower than the one of their more risky suppliers, thus allowing them to access short-term credit at a lower cost (Yu, Huang, and Guo 2020).

The opportunities of financial services through proposed AI-enabled supply chain networks (Ouyang and Li 2010), as AI technologies in supply chain management (SCM) become popular, global FDIs are aspiring to implement AI in their supply chain networks, especially for financial services (Xing et al. 2010). AI can help develop sustainable financial services by improving performance and maintaining FDIs – supplier-customer partnerships. Although existing supply networks are mainly used to conduct operations such as moving goods from suppliers to factories or sending finished products to customers, the amount of data generated during these transactions are assets/resources that can be used during the technological implementation and financial services. FDIs operation exist in multiple layers; thus, the network requirements and financing also vary at each layer and by network (Cheung et al. 2004). Therefore, AI in existing supply networks offers an environment for data analysis and optimum financial services. FDIs are expanding across the globe; in tandem, supply networks are also expanding and becoming more dependable by leveraging alternative sources of financing to sustain operations and growth. Innovative technology such as AI enhances supply chain finance partnerships between financiers and FDIs dependent on supply chain network activities. Prior studies suggest that supply networks are one of the most reliable and sustainable areas of a supply chain that can support

financial services (Caniato, Henke, and Zsidisin 2019; Carnovale, Rogers, and Yeniyurt 2019).

In this study, we develop a meta-framework based on extant literature in supply chain networks, supply chain finance, and AI technologies. We also conduct an online survey for data collection, data analysis results in this study suggest that the implementation of AI directly with SCF is not supported. However, the implementation of AI with SCNs is support as well as the implementation of AI, SCNs, and SCF. These results further suggest that technogical advancements such as AI lead to a sustainable financing for the FDIs. The final section of the paper presents the implications of the study, limitations, and paths for future research.

2. Literature review

The food and drink supply chain has been struggling with financial support since the 2008 economic recession (Gelsomino Luca et al. 2016). In this context, scholars have explored factors such as supply chain finance risks (Coulibaly, Sapriza, and Zlate 2013), supply chain finance opportunities (Bals 2019), food and drink firms (Yakovleva, Sarkis, and Sloan 2012), and supply chain networks (Osadchiy, Gaur, and Seshadri 2015). Accordingly, this study reviews the literature on supply chain finance, supply chain networks, and AI theories to develop a meta-framework based on the identified lacunae in research.

2.1 Supply chain finance

Regarding financial services in the food and drink supply chain, there exist many phenomena related to SCM including information, cash flows and goods, which hold research importance for FDIs (Nagurney, Li, and Nagurney 2013). While there is considerable research on cash flows, transactional data and information management in supply chains (Park and Park 2003); it is also important to understand financial services that are available to FDIs. Data from goods and cash flows are integrated into this discussion as well (Robu and Flynn 2017; Ruiying et al. 2017; Tunca and Zhu 2018).

Limited access to finance challenges the food and drink industries in dealing with, for example, the operations of routine activities, meeting increasing customer demands and dealing with suppliers (Xu et al. 2018). The last financial crisis left a gap in the cash flows for FDIs; hindering customers demand fulfilment, which, in turn, led to a shortage of goods in the market, with the food and drink industries needing financial services from financial institutions or brokers (Yakovleva, Sarkis, and Sloan 2012; Yu, Li, and Yang 2017). Given these challenges, financial institutions and brokers changed the standards and requirements of the application processes. These changes further increased difficulties for food and drink supply chains, including the narrowing of their cash flows (Zhan, Li, and Chen 2018; Cornett et al. 2011).

As customer demand continues to grow, FDIs need to find sustainable cash flows to meet demand. According to Kapelko (2019), post-recession supply chain finance is designed to support the supply chain by providing financial services at low-interest rates and with respect to cash flows and other financial activities. Dora et al. (2019) argue that the principles of supply chain finance are a fundamental component of a sustainable food and drink supply chain. Financial institutions and brokers do offer credit and trade financial supports to speed up food and drink operations (Yakavenka et al. 2019), although these services have no long-term sustainability. Carnovale, Rogers, and Yeniyurt (2019) suggest that credit and trade financial services under supply chain finance are a short-term solution that could boost the turnaround time of food and drink supply chain operations and reduce the risks of interruptions.

Commercial financial giants can benefit food and drink supply chain financing. They can combine the inventory and financial systems into a single integrated operations and finance system, wherein cash flows are provided based on need and level of operation (Bals 2019; Song et al. 2019). In this vein, Hennelly et al. (2020) state that B2B financing under supply chain finance offers trade credit and crowdfunding to support the food and drink supply chain. In practice, FDIs supply chain is increasing as a response to increasing customer demand. This trend necessitates long-term sustainable financing. However, insufficient cash flows are a common issue in food and drink supply chain operations and financial problems. There is an opportunity for technological innovation that can alleviate some financial difficulties, especially cash flow issues (Pfohl and Gomm 2009; Kouvelis and Zhao 2012).

2.2 Supply networks

Supply networks provide channels for information, transfer, management, and exchange of goods and services in the food and drink supply chain, whereas supply chain networks with technological innovation enable supply chain finance processes (Russell and Norvig 1995). In supply networks, supply chain partners benefit from multiple resources from the same channels, which enhances efficiency, productivity, and collaboration (Pyo and Lee 2018; Fattahi 2020). FDIs are interested in integrative innovations in supply chain networks wherein access to financial services is included in the opportunities available via this channel (Mizgier, Wagner, and Jüttner 2015) and the operations, suppliers and customers are connected.

According to Wang and Hu (2017), the resource dependency theory is important for maximising supply network resources for optimum efficiency and productivity. Further, the network environment also helps establish an understanding of all parties'

operational needs in order to maintain working relationships. The perspective of the food and drink supply chain on network environment is fundamental for resource sharing, especially when FDIs and supplier networks are interconnected (Nair et al. 2018). Hence, the relationships between FDIs, suppliers and financial service providers are defined based on an overall aim to build sustainable supply networks while assuming the new structure combines existing networks and, ultimately, creates common resources (D'Ignazio and Giovannetti 2014).

Wu et al. (2012) argue that the resource dependency theory is the fundamental concept for building sustainable networks that can enable supply chain resource sharing. The history of supply chain network structures and development also reveals opportunities to consider financial services. In supply chain networks, we find a proposal for an innovative method that unveils a new structure for global financing; numerous studies suggest the need to interconnect FDIs, suppliers, and financial services into one efficient bundle of networks (Ouyang and Li 2010; Osadchiy, Gaur, and Seshadri 2015; Basole et al. 2017). Song et al. (2019) follows the same line of inquiry to identify the role of network brokerage. They suggest that FDIs need to expand existing supply networks structure to connect with supplier networks globally, and this can occur through advanced technologies and information management. The literature also examines how FDIs govern and negotiate control with partners and suppliers to facilitate resource sharing, or the position of food and drink supply chains in the operations of innovative networks (Xu, Liu, and Wang 2008).

FDIs accessing financial services through networks suggest consistency, reliability, and dependability in the smooth operations of day-to-day activities (Marn-Ling et al. 2007). Supply chain networks driven by technology are highly beneficial to the food and drink supply chain, as they allow greater access to financial services owing to network-assured guarantees (Nair et al. 2018). The dominant view on resource dependency theory is that it is significant for FDIs and suppliers in order for them to have consistent access to shared resources and funding; which, in turn, ensures customer demands are met (Carnovale, Rogers, and Yeniyurt 2019). However, supply chain networks need to welcome interdependencies in products, cash flows, resource flows and information flows. Such dependencies in the food and drink supply chain networks open new opportunities for FDIs and suppliers to sustain links by committing to AI-driven supply networks.

Some studies explore interdependencies that are both positive and negative for food and drink supply chain operations and then emphasise opportunities for further research (Radhakrishnan et al. 2018; Cuervo-Cazurra, Mudambi, and Pedersen 2019; Taylor, McLarty, and Henderson 2018). According to Ouyang and Li (2010), interdependencies are a continuous process in which FDIs and suppliers promote new inter-cooperation in resource and information sharing. However, the degree of interdependencies is also a risk in resource dependency theory, and mitigating factors are established to manage and control risk (Yu, Li, and Yang 2017). AI-enabled supply chain networks are an emerging global phenomenon; along with this, a business continuity plan should be formed to tackle initial issues that may arise (Palsule-Desai, Tirupati, and Chandra 2013; Basole et al. 2017).

2.3 Artificial Intelligence

The supply chain sector is poised to benefit greatly from technological advancements; the food and drink supply chain is especially embracing this change by implementing innovative technologies like AI in supply networks, and thus changing the way operations are conducted (Luger 2005). AI can function as hardware and/or software in a system that represents human intelligence; this type of integration is increasing in all business operations, as firms become more dependent on technological innovations (Jain 2009; Min 2010). For example, the car manufacturing sector introduced autonomous driving systems to assist or support drivers and passengers on their journey; the aim is to enhance safety and safe driving experiences. Thus, AI technologies and applications are supporting supply chain operations, machineries, and procedures in SCM (Xing et al. 2010; Fan et al. 2020; Radhakrishnan et al. 2018; Ruiying et al. 2017). The impact of introducing new developments such as AI will not only bring innovation and advancement but also affect the workforce in the FDIs, where employees require training and new skills to embrace the new way of getting work done.

Operations in the food and drink supply chain require interactions between workers and machines; the class of these interactions varies by the complexity of the intelligence in the supply networks (Gunasekaran and Ngai 2014). In the literature, intelligence is defined as the process or ability to acquire expertise through experiences or skills, which is then applied to real-life circumstances and, thereafter, provides added benefits (Dirican 2015; Thuermer 2016; Ehteram et al. 2017; Klumpp 2018). It is also the ability to create seamless results through technology, data processing, and complex problem-solving, which require skills and knowledge in the domain of human intelligence (Baryannis et al. 2019).

AI theories focus on innovations in machine intelligence that can support business and supply chain activities (Fan et al. 2020; Radhakrishnan et al. 2018; Ruiying et al. 2017). For example, demand and inventory management are a crucial part of food and drink supply chain strategies. AI provides forecasting tools through machine learning, which offers an endless predictive analysis of big data to improve decision-making (Huang, Li, and Fu 2019).

AI consists of many components – the most important component for the food and drink supply chain is the humanlike feature of analytics (Fan et al. 2020; Radhakrishnan et al. 2018; Ruiying et al. 2017). Scholars have shown that firms that have implemented at

least one form of AI technology to their operations saw a growth increase of 10 percentage (Foresti et al. 2020; Fan et al. 2020). Thus, the predictive growth rate for FDIs can increase by the same percentage with AI-driven innovations.

Mekov, Miravitlles, and Petkov (2020) suggest that AI technologies can boost productivity and support many operational sections of the food and drink supply chain, especially supply networks. The attributes of AI technologies, such as human intelligence, analytics, forecasting, and optimisation, are crucial for building sustainable supply chain financing with supply networks (Patnaik 2015; Zahraee, Khalaji Assadi, and Saidur 2016). AI technologies include knowledge networks wherein data are stored, processed, and analysed; the rules of engagement during interactions and resourcefulness are managed herein (Moraga, Trillas, and Guadarrama 2003; Wright and Schultz 2018). The knowledge networks monitor the activities of the systems that support operations in the food and drink supply chain.

2.4 Food and drink supply chain meta-framework

Supply chain requirements comprise of the food and drink supply chain inventories records, including operational requirements like daily cash flows and suppliers' requests. The inventories monitor and ensure sustainable working capital that supports daily supply chain operational requirements (Xu et al. 2018; Tunca and Zhu 2018). Here, FDIs and suppliers prioritise effective control and monitoring of financial activities. The cash flow is an important resource that is required for daily operations in the food and drink supply chain as it supports transactions between FDIs and suppliers while also keeping the business afloat (Li et al. 2019). Therefore, this study will be seeking answers to the following research questions (RQs) developing through this study's literature section:

```
RQ1. Why is AI important for the sustainability of SCF using SCNs?
```

```
RQ2. How does moderating the integration of AI and SCNs promotes sustainable SCF?
```

Also, this study developed a meta-framework from the preceding literature review on supply chain finance, supply chain network, and AI. Together, these three strains of theory allow us to find possible relationships. Table 1 summarises the contributions of the relevant research, particularly with respect to each perspective identified in the meta-framework.

Table 1. Summary of the Theory Review.

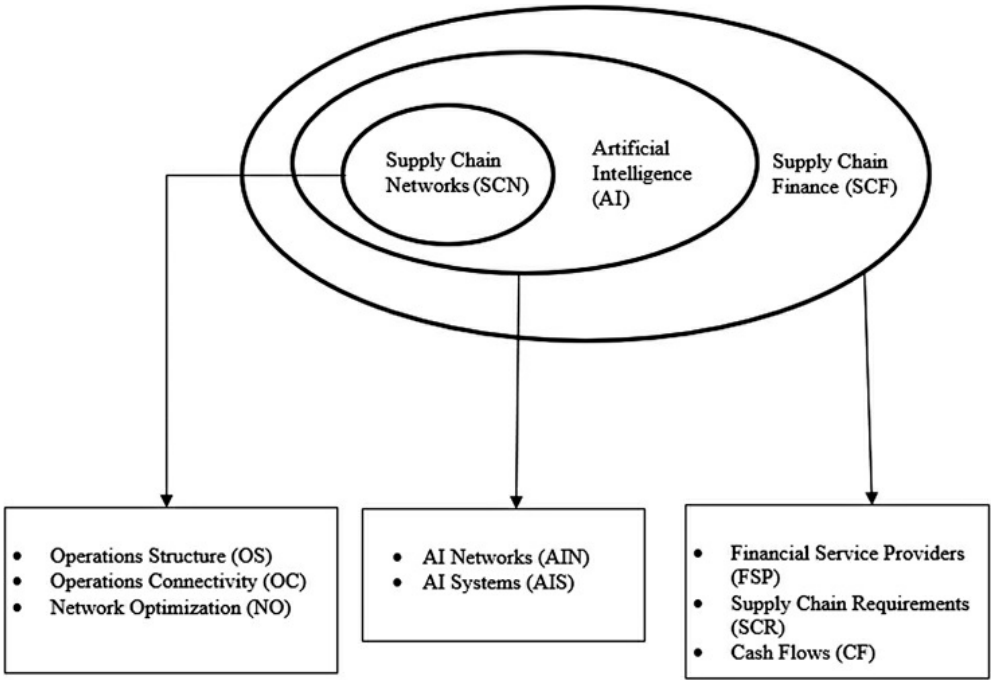
Citations (category order)	Research Context	Research aims	Benefit to supply chain finance	Benefit to supply chain network	Benefit to AI
(Yakavenka et al. 2019; Dora et al. 2019)	Food and Drink Industries	In-depth comprehensive literature review of studies on sustainable operations, supply chain, and food products	Building conceptual frameworks and models to enhance the understanding of financial services and funding	Finding associations from supply networks literature to support the meta-framework in this research	Supports investigations of the relationships defined for constructs of supply chain financing and supply chain network
(Caniato et al. 2016; Zhao and Huchzermeier 2015)	Supply Chain Finance	Understanding the operations of finance interface models, sustainable financial services and decision-making	Literature linking conceptual frameworks and models with financial service activities, sustainability, and optimisation	Finding associations from supply chain financing and artificial intelligence literature to support the meta-framework in this research	Supports investigations of the relationships defined for constructs in the supply chain finance perspective

(Thuermer 2016; Gunasekaran and Ngai 2014)	Artificial Intelligence	Technology strategies, models, and implementations incorporating new innovations in twenty-first century supply chain planning and control	The holistic approach presented compares the traditional financial services with technology-driven financial services	Finding associations from the Artificial intelligence literature to support the meta-framework in this research	Supports investigations of the relationships defined for artificial intelligence literature
(Song et al. 2019; Carnovale, Rogers, and Yeniyurt 2019)	Supply Chain Networks	In-depth comprehensive literature review of studies on sustainable operations, networks optimisation, and sustainable networks	Building conceptual frameworks and models to enhance the understanding of financial services and funding within supply networks	Finding associations from supply networks literature to support the meta-framework in this research	Supports investigations of the relationships defined for supply chain network

Prior works have detailed diverse views on supply chain finance for FDIs. Yet, all reach consensus that support with cash flows for operational purposes (Caniato et al. 2016; Pfohl and Gomm 2009).

For our meta-framework, we identify three constructs – financial service providers, supply chain requirements, and cash flows – from the literature on supply chain finance (see Figure 1).

Figure 1. Food and drink supply chain meta-framework.



FDI requirements for financial services depend on global demand. However, the requirements in the application processes are complex and time-consuming (Bals 2019; Lekkakos and Serrano 2016). Financial service providers mainly focus on firms' incoming and outgoing cash flows, but most often they do not consider supply networks as tangible and valid resources.

Both supply chain network and AI perspectives are strategically integrated to achieve sustainable, technology-driven supply networks. Here, there are three constructs – operations structure, operations connectivity, and network optimisation – associated with the supply chain network perspective and two constructs for the AI perspective (see Figure 1). Ouyang and Li (2010) suggest that conventional supply chain networks support supply chain operations by focusing on existing resources. This establishes long-term relationships and partnerships between FDIs and suppliers. Other scholars argue for an innovative supply chain network that is driven by innovative technology such as AI (Thuermer 2016; Dirican 2015).

There are emerging opportunities for the development of innovative and technology-driven supply chain networks that can support sustainable financing. Figure 1 suggests that when AI is embedded into existing supply chain networks, the existing information in the supply networks seamlessly improves the intelligence of supply chain networks. This way, a resourceful channel

for financial services can be established.

2.5 Configuration approach for supply chain meta-framework

The fsQCA configuration approach (Figure 1) adopted for this study has been supported by empirical research. For instance, this research is an effort developed to test the existence of equifinality, arguing that there is more success in the combination of SCN and AI in supply chain, specifically on financing in the FDIs. The equifinality theory advances support to FDIs' ability to make strategic decisions (Woodside 2013). In addition, along with Casillas and Martínez-López (2009) concept on equifinality in fsQCA, Figure 1 proposed an extension to the SCN theory by integrating AI components, which allows for storage, retrieval and analysis of data generated from SC operations which can benefit FDIs. FDIs market environment is partly exogenous and partly subject to influence by the transactions happening via the networks, making strategic choices therefore impact on access to financing (Caniato et al. 2016; Zhao and Huchzermeier 2015).

The existence of a relationship between SCN and SCF by linking the use of technological advancements such as AI, emphasising Song et al. (2019) concept on 'network brokerage' and Kapelko (2019) on 'competitive strategy for financing' with its implications for gaining access to financial resources, especially the generation of cash flow. This research approach supports the theory that a high innovative propensity leads to a chain of financing opportunities at the networks level on SCM, which in turn aggregate into the FDIs' persistent expansion.

fsQCA configuration research, this study adopts complimentary and equifinality approach in the design of the three propositions;

Proposition 1: A high support level for the integration of FDIs networks and AI technologies. At least one typology of the combinations is a sufficient condition for data sharing to achieve a high level of assets valuation for sustainable cash flow.

Proposition 2: Relationship mapping of components from the supply chain meta-framework to establish true associations of valid entities. As part of proposed sustainable SCF that has a high support level of at least one proposed SCN relationship is a sufficient condition for AI integration to achieve a high level of operational data corresponding with that type of financing.

Proposition 3: Verification of the combined solution pathway for associations of SCF, AI and SCF in the supply chain meta-framework. performance dimension corresponding with that combination.

3. Research method

3.1 Research design and data collection

In this study, we conducted an online survey for data collection on FDIs, supply chain finance, supply chain network with AI experts, managers, and researchers around the globe. We used Qualtrics to invite participants to participate (see Table 2). Over 563 respondents responded to the questionnaire. We particularly sought food and drink professionals, experts, and researchers, as well as professionals and researchers in AI, supply chain, and supply chain financial services with at least one-year working experience in any one of the following fields: food and drink supply chain, supply chain network management, supply chain financial management, or supply chain-related technology and innovations. The participants were informed of the study goals; the survey was scrutinised by expert panellists in the areas of food and drink supply chain, supply chain network management, supply chain financial management, or supply chain-related technology and innovations. At the end of the online survey process, 233 respondents successfully completed the surveys (41% response rate). Prior to the full data collection, we completed preliminary testing with five samples.

Table 2. Participants' profile.

	No.	Percent		No.	Percent
Gender			Supply chain finance, supply chain network, and AI experience		
Male	148	63.4	Less than a year	18	7.6
Female	85	36.6	1–2 year(s)	24	10.5
			3–4 years	42	18.2
Age			5–6 years	53	22.7
18–24	17	7.2	7–8 years	52	22.3
25–34	37	15.9	9–10 years	25	10.6

35–44	59	25.5	More than 10 years	19	8.1
45–54	72	30.8			
55–64	45	19.1			
65 or above	3	1.5			
Location					
Africa	29	12.5			
Asia	41	17.5			
Australia plus Oceania	30	12.7			
Europe	60	25.8			
North America	68	29.4			
South America	5	2.1			

Each perspective has at least two constructs as outlined in our meta-framework. For data collection, we implemented a seven-point Likert scale ranging from 'strongly disagree' (1) to 'strongly agree' (7) in order to test for complementarity and equifinality. Data analysis was conducted using fuzzy set analysis (fsQCA).

3.2 Fuzzy set analysis

The fsQCA discovers complimentary and equifinality in the data analysis, as both are similar in the underlying assumption in patterns of constructs that demonstrate various features and outcomes, depending on the structures of the associations on the constructs (Klashanov 2018). Attributes within a relationship are arranged in conditions (present or absent) and connected; rather than the overall effect of all the attributes, we consider standalone items for analysing the result. Complementarity occurs when attributes show causal factors that match and support a higher level of outcome. Similarly, when defining equifinality, at least two different pathways – known as combination of causal factors – generate the same level of result. Nevertheless, the discussion on FDIs, supply chain finance, supply chain network, and AI technologies highlights the characteristics of causal asymmetry and equifinality. Previous studies that used the econometric method for data analysis depend on casual symmetry and the assumption of unifinality since there is a lack of an alternative method that supports casual asymmetry and the equifinality assumption (Shipley et al. 2013; Ragin 2009).

fsQCA is an analytic technique that studies causal complexity, focusing on the outcomes of the conditions (necessary and/or sufficient) for a set-theoretic approach using Boolean algebra (Ragin and Pennings 2005). Also, it has a set logic of two potential outcomes: method of agreement or method of difference (Schmitt, Grawe, and Woodside 2017; Woodside 2013). Thus, fsQCA emphasises causal patterns by exploratory set-subset relationships. Casillas and Martínez-López (2009) argue that members in a set and the combinations of attributes that are linked with the casual complexity using Boolean algebra permit reduction in the casual conditions and set of combinations.

Conventional approaches use a given population sample and consider the set-theoretic technique by distributing constructs of each perspective with another, which helps develop both positive and negative relationships. For example, relationships that are not supported by the results are classified as negative relationships based on testing with the available data; on the other hand, they can generate results that are supported by another set of data (De Santis, Rizzi, and Sadeghian 2017).

4. Data analysis and results

The constructs in the three perspectives of supply chain finance, supply chain network, and AI technologies (see Figure 2) identify the important role of relationship mapping (Arshad, Islam, and Khaliq 2014). This suggests a trade-off in some of the deviations from the proposed meta-framework. Here, three deviations are significant in the fsQCA analysis: external validity, empirical context, and alternative theory (Azadi et al. 2009).

(1). External validity: It is most difficult to set the required measurement when there are unclear questions. This makes it challenging for participants to answer questions correctly. To tackle this problem, pilot testing is conducted with a small sample size for a professional and researchers in the three research areas in order to clarify the questionnaire.

(2). Empirical context: In cases where any relationship mapping demonstrates weak support owing to some specific features in the context, the validity of the relationships is considered inconclusive in the meta-framework based on the empirical data gathered to validate the mapping. An example is a case that indicates the data result as weak support than differentiated results on specified data; thus, the findings cannot be generalised. To mitigate this challenge, the relationship in the meta-framework can be repeated using empirical context with different perspectives for the data analysis (Rikhtegar, Javidan, and Keshtgari 2017; Karatop, Kubat, and Uygun 2015).

(3). Alternative theory: This refers to proposing explanations to understand the specific phenomenon that can occur because of different factors that are available in the proposed meta-framework or using a completely different casual factor.

(4). The process flow chart in Figure 3 indicates how relationship mapping is validated using Boolean algebra to classify the level of support, ignore, or reject each association of constructs.

Figure 2. Integrated meta-framework.

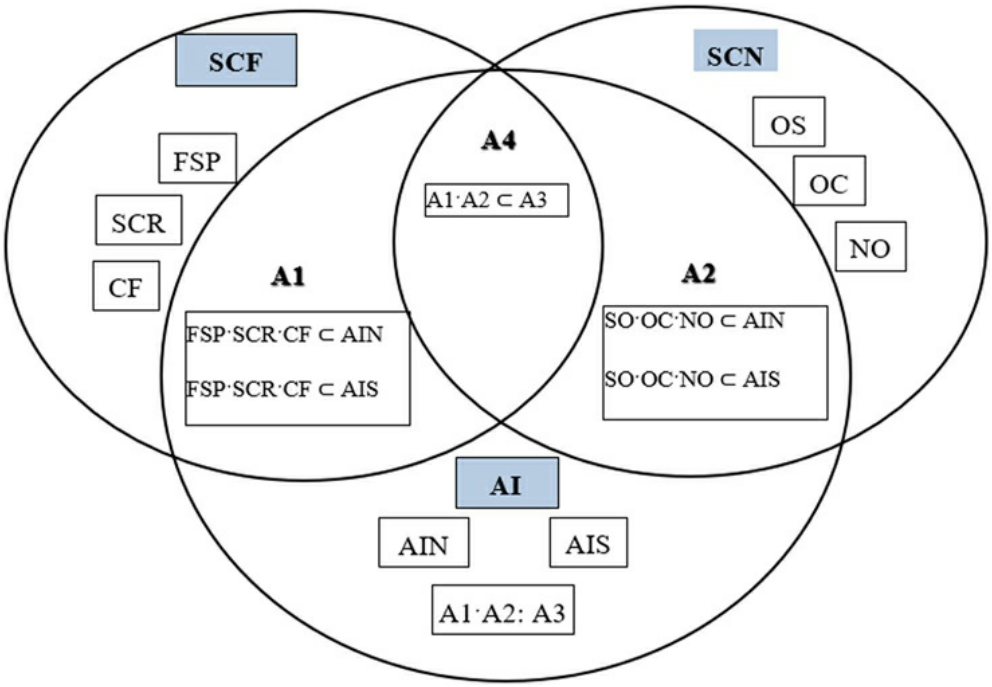
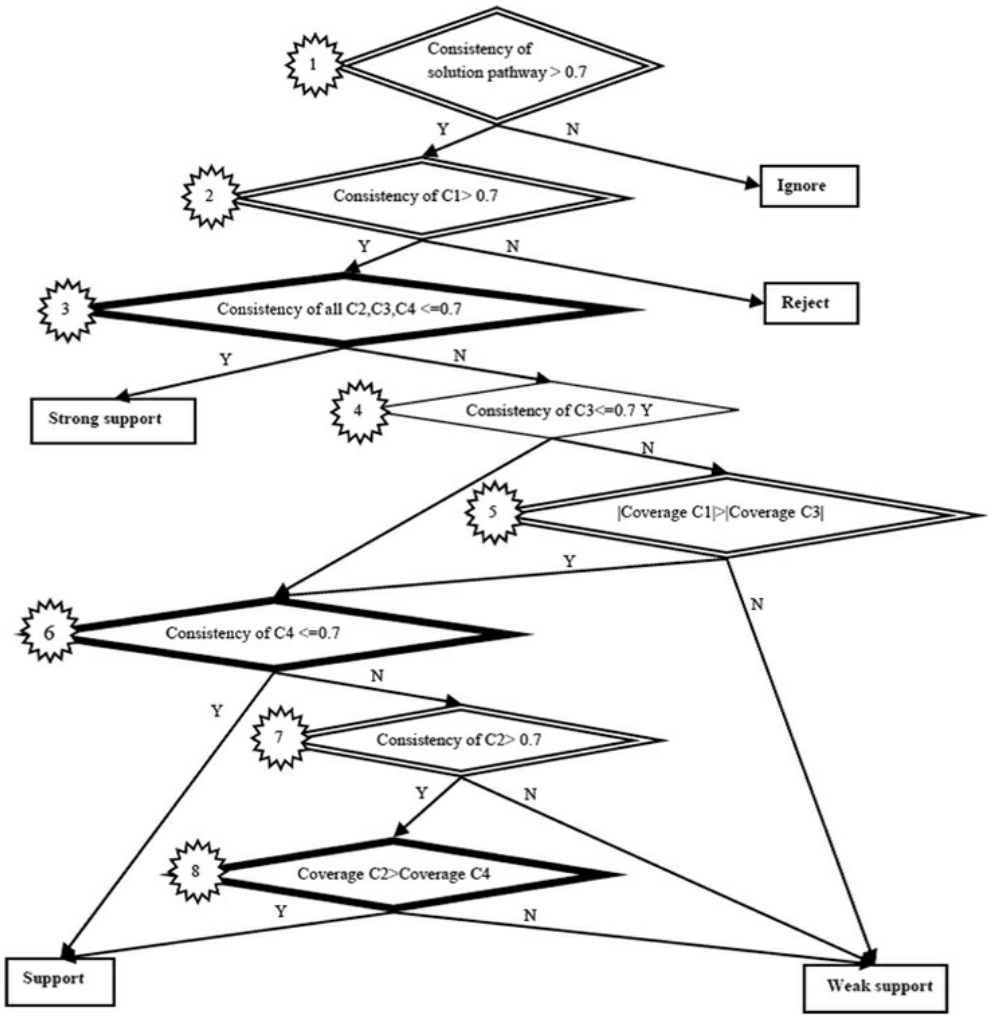


Figure 3. Flow chart for consistency analysis.



Sufficiency analysis of the survey data supports combinations of three conditions that forecast consistency threshold, consistency, and coverage for all solutions (see Table 3).

Table 3. Results for A1: Association of Artificial Intelligence and Supply Chain Finance.

	A1: FSP·SCR·CF/AIN		A1: FSP·SCR·CF/AIS					
Condition	S1	S2	S1	S2	S3	S4	S5	S6
Consistency	**0.710821**	**0.707768**	**0.765686**	**0.765449**	**0.744607**	**0.721643**	**0.752359**	**0.724879**
Raw coverage	0.161335	0.141693	0.271478	0.276201	0.122971	0.135516	0.176421	0.122943
Unique coverage	0.133212	0.113569	0.005228	0.009829	0.000000	0.014413	0.059603	0.020313
Solution consistency	0.698729		**0.737556**					
Solution coverage	0.274904		0.433273					
C1: H•S⊂Y-Consistency	0.577474	**0.885895**	**0.741731**	**0.742281**	**0.738684**	**0.741347**	0.661336	0.632467
C1: H•S⊂Y – Raw coverage	0.037379	0.019773	0.067693	0.067888	0.036445	0.060719	0.076477	0.052048
C2: ~H•S⊂Y – Consistency	***0.707803***	***0.707659***	***0.758817***	***0.758912***	***0.741195***	***0.720002***	***0.751887***	***0.721963***
C2: ~H•S⊂Y – Raw coverage	0.160089	0.142945	0.261769	0.266685	0.121413	0.135352	0.174923	0.121360

C3: H•~S⊂~Y – Consistency	0.592729	0.592729	0.646881	0.646881	0.638187	0.638187	0.638187	0.638187
C3: H•~S⊂~Y – Raw coverage	0.389349	0.389349	0.400526	0.400526	0.400526	0.400526	0.400526	0.400526
C4: ~H•~S⊂Y – Consistency	0.555285	0.560079	0.532188	0.529617	0.539168	0.545114	0.523206	0.528620
C4: ~H•~S⊂Y – Raw coverage	0.654301	0.649741	0.607637	0.601397	0.695621	0.707863	0.673700	0.697165
Solution pathway result	Reject	Support	Support	Support	Support	Support	Reject	Reject
Combined solution pathway unique coverage of same result	0.133212	0.113569	0.02947				0.079916	
Overall result	**Reject**		**Reject**					

This endorses low consistency for most of the pathways and suggests a trade-off relationship between the unique coverages, which demonstrates conditions with the highest unique coverage (0.13). Table 4 suggests a combined solution pathway unique coverage with the highest measure of (0.47), whereas Table 5 shows the highest unique coverage (0.17). Table 6 endorses a combined solution pathway unique coverage (0.09).

Table 4. Results for A2: Association of Artificial Intelligence and supply chain networks.

	A2: SO·OC·NO/AIN						A2: SO·OC·NO/AIS		
Condition	S1	S2	S3	S4	S5	S6	S1	S2	S3
Consistency	0.686327	**0.734068**	**0.762409**	**0.733449**	**0.769484**	**0.851297**	**0.970090**	**0.720484**	**0.821792**
Raw coverage	0.280026	0.167176	0.122587	0.167030	0.250633	0.088057	0.027005	0.476571	0.046173
Unique coverage	0.105196	0.002648	0.020246	0.005280	0.089036	0.035288	0.015458	0.443178	0.018686
Solution consistency	0.693129						**0.728978**		
Solution coverage	0.443688						0.511286		
C1: H•S⊂Y- Consistency	**0.729945**	**0.740807**	**0.861210**	**0.801838**	**0.801838**	**0.985291**	**0.990466**	**0.834103**	**0.822977**
C1: H•S⊂Y – Raw coverage	0.071538	0.022629	0.017538	0.020266	0.020266	0.006270	0.005593	0.062100	0.029947
C2: ~H•S⊂Y – Consistency	0.691858	***0.740586***	***0.760692***	***0.731484***	***0.768836***	***0.851061***	***0.959823***	***0.720516***	***0.819252***

C2: ~H•S⊂Y – Raw coverage	0.244050	0.166304	0.121164	0.166122	0.250094	0.090217	0.027701	0.476310	0.046260
C3: H•~S⊂~Y – Consistency	***0.774825***	0.560471	0.569823	0.569823	0.569823	0.569823	0.643419	0.643419	0.643419
C3: H•~S⊂~Y – Raw coverage	0.047083	0.064451	0.066951	0.066951	0.066951	0.066951	0.066426	0.066426	0.066426
C4: ~H•~S⊂Y – Consistency	0.530683	0.537898	0.534615	0.539583	0.531241	0.524059	0.452218	0.394305	0.449468
C4: ~H•~S⊂Y – Raw coverage	0.809864	0.881122	0.906462	0.880940	0.815159	0.909147	0.943653	0.600654	0.939324
Solution pathway result	Ignore	Support	Support	Support	Support	Support	Support	Support	Support
Combined solution pathway unique coverage of same result		0.152498					0.477322		
Overall result	**Support**						**Support**		

Table 5. Results for A3: Association of Artificial Intelligence components.

	A3: A1·A2/AIN					A3: A1·A2/AIS		
Condition	S1	S2	S3	S4	S5	S1	S2	S3
Consistency	**0.763913**	**0.751682**	0.690030	**0.767942**	**0.777452**	**0.705287**	**0.900013**	**0.744652**
Raw coverage	0.319791	0.224194	0.196632	0.098132	0.138411	0.135570	0.022730	0.094514
Unique coverage	0.095767	0.073882	0.002741	0.000727	0.041629	0.045524	0.013280	0.009672
Solution consistency	**0.731587**					**0.732550**		
Solution coverage	0.490663					0.158522		
C1: H•S⊂Y-Consistency	**0.778244**	**0.771931**	**0.784021**	**0.816038**	**0.761024**	**0.746731**	**0.744965**	**0.766578**
C1: H•S⊂Y – Raw coverage	0.077118	0.054361	0.058303	0.067703	0.024546	0.064645	0.003513	0.055519
C2: ~H•S⊂Y – Consistency	***0.780748***	***0.751373***	0.689291	***0.785469***	***0.774987***	0.697319	***0.889444***	***0.743557***

C2: ~H•S⊂Y – Raw coverage	0.301072	0.222829	0.196266	0.092472	0.136927	0.130335	0.023318	0.095503
C3: H•~S⊂~Y – Consistency	***0.845701***	***0.734511***	***0.734511***	***0.777085***	***0.734511***	0.638614	0.618892	0.618892
C3: H•~S⊂~Y – Raw coverage	0.081937	0.097564	0.097564	0.092290	0.097564	0.077964	0.077964	0.077964
C4: ~H•~S⊂Y – Consistency	0.529065	0.540981	0.541687	0.549152	0.538308	0.507846	0.501117	0.500067
C4: ~H•~S⊂Y – Raw coverage	0.780900	0.848994	0.858642	0.959826	0.888785	0.906775	0.936251	0.917031
Solution pathway result	Support	Support	Ignore	Support	Weak support	Strong support	Support	Support
Combined solution pathway unique coverage of same result	0.170376				0.041629	0.045524	0.022952	
Overall result	**Support**					**Strong support**		

Table 6. Results for A4: Association of Artificial Intelligence, supply chain finance and supply chain networks.

	A4: A1·A2/A3						
Condition	S1	S2	S3	S4	S5	S6	S7
Consistency	**0.770447**	**0.756489**	0.691651	0.695848	0.682610	**0.772270**	0.676070
Raw coverage	0.136668	0.185175	0.461778	0.230345	0.080959	0.090902	0.398668
Unique coverage	0.028184	0.043180	0.048283	0.037023	0.020250	0.024377	0.000000
Solution consistency	0.673365						
Solution coverage	0.692684						
C1: H•S⊂Y-Consistency	**0.748419**	**0.910834**	**0.718837**	**0.840547**	**0.739235**	**0.738335**	**0.712783**
C1: H•S⊂Y – Raw coverage	0.066208	0.063584	0.346939	0.098132	0.050418	0.065612	0.344732
C2: ~H•S⊂Y – Consistency	***0.767797***	***0.754910***	0.679861	0.694787	***0.721060***	***0.842208***	0.664079
C2: ~H•S⊂Y – Raw coverage	0.134921	0.184143	0.221752	0.228990	0.083170	0.082614	0.170646
C3: H•~S⊂~Y – Consistency	0.526228	0.526228	0.741027	0.526228	0.522128	0.525249	***0.714871***
C3: H•~S⊂~Y – Raw coverage	0.322003	0.322003	0.234046	0.322003	0.316754	0.312029	0.231289
C4: ~H•~S⊂Y – Consistency	0.464312	0.455414	0.448308	0.453566	0.477883	0.457350	0.456913
C4: ~H•~S⊂Y – Raw coverage	0.630372	0.578735	0.565748	0.558827	0.665093	0.647251	0.612720
Solution pathway result	Support	Support	Ignore	Ignore	Ignore	Support	Ignore
Combined solution pathway unique coverage of same result	0.095741						
Overall result	**Support**						

Complementary shows support for the relationships in Tables 4–6, while there exists weak support in the relationships in Table 3. However, condition S2 demonstrates support for the solution pathway. The relationship testing reconfirms these solutions, highlighting high consistency in Tables 4–6 for all pathways and indicating an overall support in all the outcomes; Table 3 suggests otherwise.

Deviations in Tables 3–6 probably occur only through alternative theory. To understand the consistency and coverage clearly, it is important to note the validity of the equifinality of each table because the outcomes of the attributes from all the perspectives (supply chain finance, supply chain network, and AI technologies) share similar objectives. However, since Table 3 examines the combination of supply chain finance and AI perspectives, the attributes of the AI perspective by themselves are insufficient to advance financial services. Thus, AI can only be efficient when there are interactions with attributes from supply chain network perspectives; the AI 'do not care' condition, as a peripheral, can be ignored. That is, AI requires supply chain finance and supply chain network as part of the combination to reach high efficiency.

Hence, the results in Table 3 are not completely beyond expectation in considering all the constructs of supply chain finance as well as the supply chain network (which is rejected), which has a 'do not care' condition or is peripheral in the solution pathway. Table 3 is weakly supported because of the weak explanatory controls in the attributes of the two perspectives in the relationships.

All the constructs shown in Tables 4–6 are supported; thus, the complementarity of the proposed combinations of supply chain finance, supply chain network, and AI technologies is a common sufficient condition that generates high interactions between financial services and AI. Equifinality exists, as complementarity between the proposed combinations of AI and supply chain finance is significant for financial capability, which is sufficient to generate information through supply networks.

5. Discussion

Through a detailed review of the literature and data analysis based on a questionnaire, we established a food and drink supply chain meta-framework to understand the role of AI in developing supply networks for sustainable financial services. We considered operational activities that are processes and procedures requiring channels such as operational networks. The data analysis from our validated questionnaire presents significant outcomes. We thus evaluate the relationships developed from the three perspectives explained earlier. First, as per Table 3, the constructs from supply chain finance and AI technologies perspectives in the solution pathway result are rejected. Thus, information on the operations, cash flows, and partnership are missing in this association. Second, according to Hennelly et al. (2020), the role of AI technologies in supply chains requires sufficient availability of information flow and business processes. Table 4 indicates support for the supply chain network and AI perspectives. Here, the constructs' associations have consistency and coverage equal or above the requirement. Particularly, only S1 (*see* notation in Table 4) was ignored from the result, implying that the constructs of supply chain network and AI technologies are supported in our meta-framework. Martinez et al.(2019) state that implementation of technologies in the supply chain improves how operations are conducted; it directly affects productivity owing to the use of technological algorithms and analytics on complex operations. Thus, efficiency is easily achieved.

5.1 Why is AI important for the sustainability of SCF using SCNs?

In this study, we have analysed, using fsQCA study methodology, the application of advanced technology such as AI to provide answer to the RQs stated in section 2.4. the level of digitalisation in SC is constantly improving across every sub-division in FDIs. In fact, there are remarkable advancements in the application of teachnologies transversing the sector (Gunasekaran et al. 2018). However, the result in Table 3 demostrates a low support for AI and SCF integration only, meaning that the importance of a digital finance process as an enabler for complex transactions do not exist currently. According to Surana et al. (2005), SCF solutions are designed to manage most complex solutions at a high level of digitalisation in financial processes, however to obtain a sustainable SCF solutions, Table 4 suggests that data and information available through SC networks are necessary resources for implementing an AI driven financial solutions for the FDIs. The relevant role of AI in solving inefficient solutions in the FDIs financial processes is the digitalisation of the SCF solutions which is highly dependent on the data available via SC networks (Mizgier, Jüttner, and Wagner 2013).

5.2 How does moderating the integration of AI and SCNs promotes sustainable SCF?

According to Yu, Li, and Yang (2017), one of the long-existing issues in SC is the problem of aligning physical and financial processes in the FDIs. Table 5 suggest in the findings that most FDIs supports digitalisation in SCF solutions in providing a long-lasting improvement in their financial performance. Furthermore, the risk of bankruptcy can be reduced by sourcing funding through the SC networks available in the FDIs (Dolgui, Ivanov, and Sokolov 2020). This result shows a significant implication for both managerial and scholarly insight, as this study recommends rather than focusing only on finance as the only solution to the SC financing challenges but to seek sustainable SCF solutions by positioning the whole spectrum of SCF perspectives available in

the SC networks. The major advantage of sourcing SCF through SC networks is that the gaps in financing for FDIs are tackled not only for financial products but also providing opportunities on a wider spectrum (Gunasekaran et al. 2018).

Our results reinforce the value of implementing AI technologies in supply networks to support financial services for FDIs. In practice, AI advances the understanding of complex issues in a system, suggesting the importance of alternatives financial services (Yakavenka et al. 2019). However, besides other benefits for the network, the partnership between FDIs and suppliers strengthens through sharing available financial resources (Venkatesh et al. 2019; Taleizadeh, Tavassoli, and Bhattacharya 2020). AI brings together FDIs and supplier networks for financial services sharing, especially given the supply chain finance criteria and regulations of financial institutions and brokers. The power imparted to parties in resource sharing ensures specific dependence controls. This helps strike a necessary balance; access to resources available on the networks becomes mutually beneficial to all parties; and there are performance monitoring measures in place (Oyemomi et al. 2019). Importantly, there is a need to unify structures and operations in the networks into a single network system.

6. Conclusion, implications and future research

6.1 Theoretical implications

Our data analysis focused on complementary and equifinality relationships in the constructs of the three perspectives of supply chain finance, supply chain network, and AI technologies. Thus, we enable a shared understanding of the explanatory influence linking theoretical viewpoints with consistency (Wang and Hu 2017). Our meta-framework is novel; it presents complementary results that contribute to the holistic evaluation of all constructs of the three perspectives. Thus, building relationships and presenting the findings by identifying the importance of each relationship mapping could enable sustainable supply chain financing for FDIs through AI-driven supply networks (Dora et al. 2019; Devalkar and Krishnan 2019; Tseng et al. 2018).

We extend the extant literature (Fan et al. 2020; Bals 2019; Radhakrishnan et al. 2018; Ruiying et al. 2017) on FDIs, supply chain finance, supply chain network, and AI technologies. The online survey data advances the understanding of solution coverage across relationship mapping, as we analyse the complementary efficiency and equifinality. The role of AI technologies observed helps explore the conditions that differentiate the values of consistency and unique coverage in the fsQCA analysis. We also address the gap in studies on supply chain networks (the environment) and FDIs, which benefit from the cascading resources in AI-driven supply networks (Kuo and Kusiak 2019). Notably, fussy set data analytics contributes to complex causality in obtaining new empirical outcomes.

In summary, our new meta-framework is a novel contribution. It explores the implementation of technology within existing networks in the food and drink supply chain. It proposes availabilities of resources via AI-enabled networks and partnering with financial institutions and brokers, based on data suggesting the potential of untapped resources within supply chain networks.

6.2 Industry implications

We conducted a robust literature review, followed by an in-depth empirical analysis of the complimentary and equifinality of the data set. This allows researchers to gain a better understanding of the complex casualty on the significant role of technology in advancing existing supply chain networks, which permits the integration of supply chain resources and operations. Resources such as financial services can provide a solution to the challenges of cash flows, allowing for FDIs and suppliers to develop a constructive strategy for the implementation of sustainable financing that considers the values of the supply networks (Pyo and Lee 2018). In Figure 2, we put forth relationship mappings of constructs of the three perspectives by developing combinations for solution pathways in the outcomes. FDIs' prioritising of resources enables sustainable cash flows for operations and business activities. Thus, AI unravels hidden and untapped resources in supply networks (Hofmann and Johnson 2016).

The challenge of FDIs and suppliers regarding financial services necessitates the search for alternative sustainable financing options that consider operational assets such as supply networks and processes (Gelsomino Luca et al. 2016). Innovations enable financial institutions and brokers to gain analytical information on food and drink supply chain operations using AI technologies. They assist in decision-making that supports financial services based on the supply networks activities. AI technologies reduce financial risks through the use of algorithms and analytic tools that forecast where potential risks exist in the networks and operations. They analyse complex issues and risk exposures in supply chain operations, creating a rigorous intelligence system sufficient for sustainable financing.

6.3 Limitations and future research directions

The limitations in this study allow for future research opportunities. Our focus was to achieve relationship mapping of supply chain finance, supply chain network, and AI perspectives – specifically each perspective's constructs. One of the identified limitations in this study is the nature of the research which is a hybrid approach that focuses on the amalgamation of technology with SC. However, this limitation also proposes an opportunity for future research. We sought to enable sustainable food and

drink supply chain financing as one of the resources available on AI-driven supply networks. However, there are other perspectives that are not considered in this study, such as FDI strategies, supplier behaviour, and customer demand. Regarding the use of online surveys, future researchers should consider finance professionals and researchers in SCM and FDIs in order to support a robust understanding of the financial sector.

Disclosure statement

No potential conflict of interest was reported by the author(s **[Q2]**).

ORCID

Femi Olan http://orcid.org/0000-0002-7377-9882

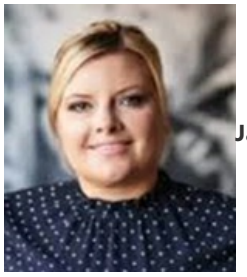
Uchitha Jayawickrama

Emmanuel Arakpogun

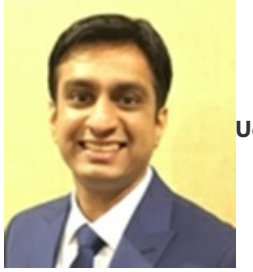
Notes on contributors

Femi Olan, PhD is a Senior Lecturer in Business Information Management at Northumbria University, UK. He obtained his PhD degree from Plymouth University, UK. He has teaching and industry experience in the field of information systems. His research interests focus on knowledge sharing, organisational factors, and performance management in organisations. He has collaborated on numerous research projects for, among others, development agencies. He has authored numerous articles in peer-reviewed journals and books.

Shaofeng Liu, PhD is Professor of Operations Management and Decision-making. She obtained her Ph.D. degree from Loughborough University, UK. Her main research interests and expertise are in knowledge-based techniques to support business decision-making, particularly in the areas of knowledge management, integrated decision support, digital business, and quantitative decision methods. She is a senior editor for *Cogent Business and Management*, an open access journal. She has undertaken several influential research projects funded by UK research councils and the European Commission with a total value of over €40 million. She is currently the PI and Co-I for four EU projects under the Horizon 2020 programme. She has published over 150 peer-reviewed research papers.



Jana Suklan, PhD is an Associate Researcher at the Translational and Clinical Research Institute at Newcastle University. She works across the University and National Institute for Health Research Newcastle In Vitro Diagnostics Co-operative. She holds a PhD in Interdisciplinary Statistics from the University of Ljubljana, Slovenia. Her thesis covered the application of econometric models for the analysis of synergetic effects within channels of integrated marketing communications. Her current work focuses on evaluations of novel medical devices from very early stages to adoption. She is professionally active in several research areas including social research, business and management, innovation, and healthcare.



Uchitha Jayawickrama, PhD is a Lecturer in Information Systems (which is equivalent to Assistant Professor) at the Information Management Group, School of Business and Economics, Loughborough University, UK.. He obtained his PhD degree from Plymouth University, UK. He has research, teaching, and industry experience in the field of information systems, particularly in the areas of enterprise systems, cloud ERP, business process automation, knowledge management, knowledge management systems, digitisation (digital innovation & productivity), business intelligence, data analytics, and business process re-engineering. He has published research in various renowned conferences, books, and journals. He is involved in several research projects internally and externally. He is a reviewer for several journals and international conferences. He has editorial experience in various journals. He is a member of several scientific/technical/program committees.

Emmanuel Arakpogun, PhD is a Lecturer in International Business Management at Newcastle Business School. His research interests lie at the nexus of the liberalisation of the telecommunications market and universal access policies as a combined strategy for closing the digital divides in emerging economies. He is a reviewer for Information Technology and People.

References

Arshad, Muhammad, Syed Islam, and A. Khaliq. 2014. "Fuzzy Logic Approach in Power Transformers Management and Decision Making." *IEEE Transactions on Dielectrics and Electrical Insulation* 21 (5): 2343–2354. doi:10.1109/TDEI.2014.003859.

Azadi, Hossein, Jan van Den Berg, Mansour Shahvali, and Gholamhossein Hosseininia. 2009. "Sustainable Rangeland Management Using Fuzzy Logic: A Case Study in Southwest Iran." *Agriculture, Ecosystems and Environment* 131 (3-4): 193–200. doi:10.1016/j.agee.2009.01.017.

Bals, Cristof. 2019. "Toward a Supply Chain Finance (SCF) Ecosystem – Proposing a Framework and Agenda for Future Research." *Journal of Purchasing and Supply Management* 25 (2), doi:10.1016/j.pursup.2018.07.005.

Baryannis, George, Sahar Validi, Samir Dani, and Grigoris Antoniou. 2019. "Supply Chain Risk Management and Artificial Intelligence: State of the art and Future Research Directions." *International Journal of Production Research* 57 (7): 2179–2202. doi:10.1080/00207543.2018.1530476.

Basole, Rahul C., Marcus A. Bellamy, Hyunwoo Park, and C. d'Aspremont. 2017. "Visualization of Innovation in Global Supply Chain Networks." *Decision Sciences* 48 (2): 288–306. doi:10.1111/deci.12213.

Caniato, Federico, Luca Mattia Gelsomino, Alessandro Perego, and Stefano Ronchi. 2016. "Does Finance Solve the Supply Chain Financing Problem?" *Supply Chain Management: An International Journal* 21 (5): 534–549. doi:10.1108/SCM-11-2015-0436.

Caniato, Federico, Michael Henke, and George A. Zsidisin. 2019. "Supply Chain Finance: Historical Foundations, Current Research, Future Developments." *Journal of Purchasing and Supply Management* 25 (2): 99–104. doi:10.1016/j.pursup.2019.02.002.

Carnovale, Steven, Dale S. Rogers, and Sengun Yeniyurt. 2019. "Broadening the Perspective of Supply Chain Finance: The Performance Impacts of Network Power and Cohesion." *Journal of Purchasing and Supply Management* 25 (2): 134–145. doi:10.1016/j.pursup.2018.07.007.

Casillas, Jorge, and Francisco J. Martínez-López. 2009. "Mining Uncertain Data with Multiobjective Genetic Fuzzy Systems to be Applied in Consumer Behaviour Modelling." *Expert Systems with Applications* 36 (2): 1645–1659. doi:10.1016/j.eswa.2007.11.035.

Cheung, Chi Fai, Wai Ming Wang, Victor Lo, and Wing Bun Lee. 2004. "An Agent-Oriented and Knowledge-Based System for Strategic e-Procurement." *Expert Systems* 21 (1): 11–21.

Cornett, Marcia Millon, Jamie John McNutt, Philip E. Strahan, and Hassan Tehranian. 2011. "Liquidity Risk Management and Credit Supply in the Financial Crisis. (Report)." *Journal of Financial Economics* 101 (2): 297. doi:10.1016/j.jfineco.2011.03.001.

Coulibaly, Brahima, Horacio Sapriza, and Andrei Zlate. 2013. "Financial Frictions, Trade Credit, and the 2008–09 Global Financial Crisis." *International Review of Economics & Finance* 26: 25–38. doi:10.1016/j.iref.2012.08.006.

Cuervo-Cazurra, Alvaro, Ram Mudambi, and Torben Pedersen. 2019. "Subsidiary Power: Loaned or Owned? The Lenses of Agency Theory and Resource Dependence Theory." *Global Strategy Journal* 9 (4): 491–501.

~~Cyrus, J Pemberton, and Lino R Correia. 2018. "Computerized Food Warehouse Automation." Computerized Control Systems in the Food Industry~~**[Q3]**~~.~~

De Santis, Enrico, Antonello Rizzi, and Alireza Sadeghian. 2017. "Hierarchical Genetic Optimization of a Fuzzy Logic System for Energy Flows Management in Microgrids." *Applied Soft Computing Journal* 60 (C): 135–149. doi:10.1016/j.asoc.2017.05.059.

Devalkar, Sripad K., and Harish Krishnan. 2019. "The Impact of Working Capital Financing Costs on the Efficiency of Trade Credit." *Production and Operations Management* 28 (4): 878–889. doi:10.1111/poms.12954.

D'Ignazio, Alessio, and Emanuele Giovannetti. 2014. "Continental Differences in the Clusters of Integration: Empirical Evidence from the Digital Commodities Global Supply Chain Networks." *International Journal of Production Economics* 147: 486.

Dirican, Cüneyt. 2015. "The Impacts of Robotics, Artificial Intelligence on Business and Economics." *Procedia - Social and Behavioral Sciences* 195: 564–573. doi:10.1016/j.sbspro.2015.06.134.

Dolgui, Alexandre, Dmitry Ivanov, and Boris Sokolov. 2020. "Reconfigurable Supply Chain: The X-Network." *International Journal of Production Research* 58 (13): 4138–4163. doi:10.1080/00207543.2020.1774679.

Dora, Manoj, Joshua Wesana, Xavier Gellynck, Nitin Seth, Bidit Dey, and Hans De Steur. 2019. "Importance of Sustainable Operations in Food Loss: Evidence from the Belgian Food Processing Industry." *Annals of Operations Research*. doi:10.1007/s10479-019-03134-0.

Ehteram, Mohammad, Mohammed Allawi, Hojat Karami, Sayed-Farhad Mousavi, Mohammad Emami, Ahmed El-Shafie, and Saeed Farzin. 2017. "Optimization of Chain-Reservoirs' Operation with a New Approach in Artificial Intelligence." *Water Resources Management* 31 (7): 2085–2104. doi:10.1007/s11269-017-1625-6.

Fan, Jingtao, Lu Fang, Jiamin Wu, Yuchen Guo, and Qionghai Dai. 2020. "From Brain Science to Artificial Intelligence." *Engineering*. doi:10.1016/j.eng.2019.11.012.

Fattahi, Mohammad. 2020. "A Data-Driven Approach for Supply Chain Network Design Under Uncertainty with Consideration of Social Concerns." *Annals of Operations Research* 288 (1): 265–284. doi:10.1007/s10479-020-03532-9.

Foresti, Ruben, Stefano Rossi, Matteo Magnani, Corrado Guarino Lo Bianco, and Nicola Delmonte. 2020. "Smart Society and Artificial Intelligence: Big Data Scheduling and the Global Standard Method Applied to Smart Maintenance." *Engineering*. doi:10.1016/j.eng.2019.11.014.

Gelsomino Luca, Mattia, Riccardo Mangiaracina, Alessandro Perego, and Angela Tumino. 2016. "Supply Chain Finance: A Literature Review." *International Journal of Physical Distribution & Logistics Management* 46 (4), doi:10.1108/IJPDLM-08-2014-0173.

Gunasekaran, Angappa, and Eric W. T. Ngai. 2014. "Expert Systems and Artificial Intelligence in the 21st Century Logistics and Supply Chain Management." *Expert Systems with Applications* 41 (1): 1–4. doi:10.1016/j.eswa.2013.09.006.

Gunasekaran, Angappa, Yahaya Y. Yusuf, Ezekiel O. Adeleye, and Thanos Papadopoulos. 2018. "Agile Manufacturing Practices: The Role of big Data and Business Analytics with Multiple Case Studies." *International Journal of Production Research* 56 (1-2): 385–397. doi:10.1080/00207543.2017.1395488.

Hennelly, Patrick A., Jagjit Singh Srai, Gary Graham, and Samuel Fosso Wamba. 2020. "Rethinking Supply Chains in the age of Digitalization." *Production Planning & Control* 31 (2-3): 93–95. doi:10.1080/09537287.2019.1631469.

Hofmann, Erik, and Mark Johnson. 2016. "Guest Editorial: Supply Chain Finance – Some Conceptual Thoughts Reloaded." *International Journal of Physical Distribution & Logistics Management* 46: 4. doi:10.1108/IJPDLM-01-2016-0025.

Huang, Shuai, Zhi-Ping Fan, and Xiaohuan Wang. 2019a. "Optimal Operational Strategies of Supply Chain Under Financing Service by a 3PL Firm." *International Journal of Production Research* 57 (11): 3405–3420. doi:10.1080/00207543.2018.1534017.

Huang, Youqin, Jiayong Li, and Jiyang Fu. 2019b. "Review on Application of Artificial Intelligence in Civil Engineering." *Computer Modeling in Engineering & Sciences* 121 (3): 845–875.

Huang, Jing, Wensheng Yang, and Yiliu Tu. 2019c. "Supplier Credit Guarantee Loan in Supply Chain with Financial Constraint and Bargaining." *International Journal of Production Research* 57 (22): 7158–7173. doi:10.1080/00207543.2019.1581386.

~~Ivanov, Dmitry, Alexandre Dolgui, and Boris Sokolov. 2019. "The Impact of Digital Technology and Industry 4.0 on the Ripple Effect and Supply Chain Risk Analytics." *International Journal of Production Research* 57 (3): 829–846. doi:10.1080/00207543.2018.1488086~~ **[Q4]**~~.~~

Jain, Vipul. 2009. "Editorial Note for the Special Issue on 'Artificial Intelligence Techniques for Supply Chain Management'." *Engineering Applications of Artificial Intelligence* 22 (6): 829–831. doi:10.1016/j.engappai.2009.01.009.

~~Jayawickrama, Uchitha, Shaofeng Liu, Melanie Hudson Smith, Pervaiz Akhtar, and Mamoon Al Bashir. 2019. "Knowledge Retention in ERP Implementations: The Context of UK SMEs." *Production Planning & Control* 30 (10-12): 1032–1047. doi:10.1080/09537287.2019.1582107~~**[Q5]**~~.~~

Kapelko, Magdalena. 2019. "Measuring Productivity Change Accounting for Adjustment Costs: Evidence from the Food Industry in the European Union." *Annals of Operations Research* 278 (1): 215–234. doi:10.1007/s10479-017-2497-0.

Karatop, Buket, Cemalettin Kubat, and Ozer Uygun. 2015. "Talent Management in Manufacturing System Using Fuzzy Logic Approach." *Computers & Industrial Engineering* 86: 127.

Klashanov, F. 2018. "Fuzzy Logic in Construction Management." *MATEC Web of Conferences* 170), doi:10.1051/matecconf/201817001111.

Klumpp, Matthias. 2018. "Automation and Artificial Intelligence in Business Logistics Systems: Human Reactions and Collaboration Requirements." *International Journal of Logistics Research and Applications* 21 (3): 224–242. doi:10.1080/13675567.2017.1384451.

Kouvelis, Panos, and Wenhui Zhao. 2012. "Financing the Newsvendor: Supplier vs. Bank, and the Structure of Optimal Trade Credit Contracts." *Operations Research* 60 (3): 566–580.

Kuo, Yong-Hong, and Andrew Kusiak. 2019. "From Data to big Data in Production Research: The Past and Future Trends." *International Journal of Production Research* 57 (15-16): 4828–4853. doi:10.1080/00207543.2018.1443230.

Lekkakos, Spyridon Damianos, and Alejandro Serrano. 2016. "Supply Chain Finance for Small and Medium Sized Enterprises: The Case of Reverse Factoring." *International Journal of Physical Distribution & Logistics Management* 46 (4), doi:10.1108/IJPDLM-07-2014-0165.

Li, Haitao, Liuqing Mai, Wenlong Zhang, and Xiangyu Tian. 2019. "Optimizing the Credit Term Decisions in Supply Chain Finance." *Journal of Purchasing and Supply Management* 25 (2): 146–156. doi:10.1016/j.pursup.2018.07.006.

Luger, George F. 2005. *Artificial Intelligence: Structures and Strategies for Complex Problem Solving*. Harlow: Addison-Wesley: Pearson education.**[Q6]**

Marn-Ling, Shing, Shing Chen-Chi, Chen Kuo Lane, and Lee Huei. 2007. "Security Modeling on the Supply Chain Networks." *Journal of Systemics, Cybernetics and Informatics* 5 (5): 53–58.

Martinez, Veronica, Michael Zhao, Ciprian Blujdea, Xia Han, Andy Neely, and Pavel Albores. 2019. "Blockchain-driven Customer Order Management." *International Journal of Operations & Production Management* 39 (6/7/8): 993–1022. doi:10.1108/IJOPM-01-2019-0100.

Mekov, Evgeni, Marc Miravitlles, and Rosen Petkov. 2020. "Artificial Intelligence and Machine Learning in Respiratory Medicine." *Expert Review of Respiratory Medicine*, 1–6. doi:10.1080/17476348.2020.1743181.

Min, Hokey. 2010. "Artificial Intelligence in Supply Chain Management: Theory and Applications." *International Journal of Logistics Research and Applications* 13 (1): 13–39. doi:10.1080/13675560902736537.

Mizgier, Kamil J., Matthias P. Jüttner, and Stephan M. Wagner. 2013. "Bottleneck Identification in Supply Chain Networks." *International Journal of Production Research* 51 (5): 1477–1490. doi:10.1080/00207543.2012.695878.

Mizgier, Kamil J., Stephan M. Wagner, and Matthias P. Jüttner. 2015. "Disentangling Diversification in Supply Chain Networks." *International Journal of Production Economics* 162: 115–124. doi:10.1016/j.ijpe.2015.01.007.

Moraga, Claudio, Enric Trillas, and Sergio Guadarrama. 2003. "Multiple-Valued Logic and Artificial Intelligence Fundamentals of Fuzzy Control Revisited." *The Artificial Intelligence Review* 20 (3-4): 169–197. doi:10.1023/B:AIRE.0000006610.94970.1d.

~~Moretto, Antonella, Laura Grassi, Federico Caniato, Marco Giorgino, and Stefano Ronchi. 2019. "Supply Chain Finance: From Traditional to Supply Chain Credit Rating." *Journal of Purchasing and Supply Management* 25 (2): 197–217. doi:10.1016/j.pursup.2018.06.004~~**[Q7]**~~.~~

Nagurney, A., D. Li, and L. S. Nagurney. 2013. "Pharmaceutical Supply Chain Networks with Outsourcing Under Price and Quality Competition." *International Transactions in Operational Research* 20 (6), doi:10.1111/itor.12031.

Nair, Anand, Constantin Blome, Thomas Y. Choi, and Gyusuk Lee. 2018. "Re-visiting Collaborative Behavior in Supply Networks – Structural Embeddedness and the Influence of Contextual Changes and Sanctions." *Journal of Purchasing and Supply Management* 24 (2): 135–150. doi:10.1016/j.pursup.2017.11.006.

Osadchiy, Nikolay, Vishal Gaur, and Sridhar Seshadri. 2015. "Systematic Risk in Supply Chain Networks." *Management Science* 62

(6): 1755–1777. doi:10.1287/mnsc.2015.2187.

Ouyang, Yanfeng, and Xiaopeng Li. 2010. "The Bullwhip Effect in Supply Chain Networks." *European Journal of Operational Research* 201 (3): 799–810. doi:10.1016/j.ejor.2009.03.051.

Oyemomi, Oluwafemi, Shaofeng Liu, Irina Neaga, Huilan Chen, and Franklin Nakpodia. 2019. "How Cultural Impact on Knowledge Sharing Contributes to Organizational Performance: Using the fsQCA Approach." *Journal of Business Research* 94: 313–319.

Palsule-Desai, Omkar D., Devanath Tirupati, and Pankaj Chandra. 2013. "Stability Issues in Supply Chain Networks: Implications for Coordination Mechanisms." *International Journal of Production Economics* 142 (1): 179–193. doi:10.1016/j.ijpe.2012.11.003.

Park, Jae Heon, and Sang Chan Park. 2003. "Agent-based Merchandise Management in Business-to-Business Electronic Commerce." *Decision Support Systems* 35 (3): 311–333.

Patnaik, Debasis. 2015. "Theorizing Change in Artificial Intelligence: Inductivising Philosophy from Economic Cognition Processes." *AI & SOCIETY* 30 (2): 173–181. doi:10.1007/s00146-013-0524-5.

Pfohl, Hans-Christian, and Moritz Gomm. 2009. "Supply Chain Finance: Optimizing Financial Flows in Supply Chains." *Logistics Research* 1 (3): 149–161. doi:10.1007/s12159-009-0020-y.

Pyo, Hanhyung, and Sangheon Lee. 2018. "Are There Spillover Effects of Large Firms' Growth in Supply Chain Networks? Evidence from the Korean Economy." *Applied Economics Letters* 25 (17): 1208–1211. doi:10.1080/13504851.2017.1412065.

Radhakrishnan, Abirami, Dessa J David, Sri V Sridharan, and John Stephen Davis. 2018. "Re-examining Supply Chain Integration: A Resource Dependency Theory Perspective." *International Journal of Logistics Systems and Management* 30 (1): 1–30.

Ragin, Charles C. 2009. *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. Chicago: University of Chicago Press.**[Q8]**

Ragin, Charles C., and Paul Pennings. 2005. "Fuzzy Sets and Social Research." *Sociological Methods & Research* 33 (4): 423–430. doi:10.1177/0049124105274499.

Rikhtegar, N., R. Javidan, and M. Keshtgari. 2017. "Mobility Management in Wireless Nano-Sensor Networks Using Fuzzy Logic." *Journal of Intelligent and Fuzzy Systems* 32 (1): 969–978. doi:10.3233/JIFS-161552.

Robu, Valentin, and David Flynn. 2017. "Outsmart Supply Dips in Renewable Energy." *Nature* 544 (7649): 161. doi:10.1038/544161b.

Ruiying, Li, Dong Qiang, Jin Chong, and Kang Rui. 2017. "A New Resilience Measure for Supply Chain Networks." *Sustainability* 9 (1): 144. doi:10.3390/su9010144.

Russell, S., and P. Norvig. 1995. *"Learning in Neural and Belief Networks." Artificial Intelligence: A Modern Approach*. Upper Saddle River, NJ: Prentice–Hall.

Schmitt, Ann Kristin, Andreas Grawe, and Arch G. Woodside. 2017. "Illustrating the Power of fsQCA in Explaining Paradoxical Consumer Environmental Orientations." *Psychology & Marketing* 34 (3): 323–334. doi:10.1002/mar.20991.

Shipley, M., M. Johnson, L. Pointer, and N. Yankov. 2013. "A Fuzzy Attractiveness of Market Entry (FAME) Model for Market Selection Decisions." *The Journal of the Operational Research Society* 64 (4): 597–610. doi:10.1057/jors.2012.59.

Song, Hua, Qiang Lu, Kangkang Yu, and Cheng Qian. 2019. "How do Knowledge Spillover and Access in Supply Chain Network Enhance SMEs' Credit Quality?" *Industrial Management & Data Systems* 119 (2): 274–291. doi:10.1108/IMDS-01-2018-0049.

Surana, Amit, Soundar Kumara, Mark Greaves, and Usha Nandini Raghavan. 2005. "Supply-chain Networks: a Complex Adaptive Systems Perspective." *International Journal of Production Research* 43 (20): 4235–4265. doi:10.1080/00207540500142274.

Taleizadeh, Ata Allah, Sara Tavassoli, and Arijit Bhattacharya. 2020. "Inventory Ordering Policies for Mixed Sale of Products Under Inspection Policy, Multiple Prepayment, Partial Trade Credit, Payments Linked to Order Quantity and Full Backordering." *Annals of Operations Research* 287 (1): 403–437. doi:10.1007/s10479-019-03369-x.

Taylor, Erik C, Benjamin D McLarty, and Dale A Henderson. 2018. "The Fire Under the Gridiron: Resource Dependence and NCAA Conference Realignment." *Journal of Business Research* 82: 246–259.

Thuermer, Karen E. 2016. "Machine Learning is Coming: Artificial Intelligence Capabilities Will Help Food Companies Make up-to-the-Minute Decisions That Can Reduce Supply Chain Disruptions.(SECTOR REPORTS: SOFTWARE & TECHNOLOGY)." *Food Logistics* 11 (182): 68.**[Q9]**

Tseng, Ming-Lang, Kuo-Jui Wu, Jiayao Hu, and Chin-Hsin Wang. 2018. "Decision-making Model for Sustainable Supply Chain Finance Under Uncertainties." *International Journal of Production Economics* 205: 30–36. doi:10.1016/j.ijpe.2018.08.024.

Tunca, Tunay, and Weiming Zhu. 2018. "Buyer Intermediation in Supplier Finance." *Management Science* 64 (12): 5631. doi:10.1287/mnsc.2017.2863.

Venkatesh, V. G., Abraham Zhang, Eric Deakins, Sunil Luthra, and S. Mangla. 2019. "A Fuzzy AHP-TOPSIS Approach to Supply Partner Selection in Continuous aid Humanitarian Supply Chains." *Annals of Operations Research* 283 (1): 1517–1550.

Wang, C., and Q. Hu. 2017. "Knowledge Sharing in Supply Chain Networks: Effects of Collaborative Innovation Activities and Capability on Innovation Performance." *Technovation*. doi:10.1016/j.technovation.2017.12.002.

Woodside, Arch G. 2013. "Moving Beyond Multiple Regression Analysis to Algorithms: Calling for Adoption of a Paradigm Shift from Symmetric to Asymmetric Thinking in Data Analysis and Crafting Theory." *Journal of Business Research* 66 (4), doi:10.1016/j.jbusres.2012.12.021.

Wright, Scott A., and Ainslie E. Schultz. 2018. "The Rising Tide of Artificial Intelligence and Business Automation: Developing an Ethical Framework." *Business Horizons* 61 (6): 823–832. doi:10.1016/j.bushor.2018.07.001.

Wu, Yifan, Ming Dong, Tijun Fan, and Shaoxuan Liu. 2012. "Performance Evaluation of Supply Chain Networks with Assembly Structure Under System Disruptions." *Computers and Operations Research* 39 (12): 3229–3243. doi:10.1016/j.cor.2012.04.006.

Xing, Bo, Wen-Jing Gao, Kimberly Battle, Tshildzi Marwala, and Fulufhelo V. Nelwamondo. 2010. "Artificial Intelligence in Reverse Supply Chain Management: The State of the Art." Webist 2009: *Proceedings of the Fifth International Conference on Web Information Systems and Technologies*.

Xu, Xinhan, Xiangfeng Chen, Fu Jia, Steve Brown, Yu Gong, and Yifan Xu. 2018. "Supply Chain Finance: A Systematic Literature Review and Bibliometric Analysis." *International Journal of Production Economics* 204: 160–173. doi:10.1016/j.ijpe.2018.08.003.

Xu, Jiuping, Qiang Liu, and Rui Wang. 2008. "A Class of Multi-Objective Supply Chain Networks Optimal Model Under Random Fuzzy Environment and its Application to the Industry of Chinese Liquor." *Information Sciences* 178 (8): 2022–2043. doi:10.1016/j.ins.2007.11.025.

Yakavenka, Volha, Ioannis Mallidis, Dimitrios Vlachos, Eleftherios Iakovou, and Zafeiriou Eleni. 2019. "Development of a Multi-Objective Model for the Design of Sustainable Supply Chains: The Case of Perishable Food Products." *Annals of Operations Research*. doi:10.1007/s10479-019-03434-5.

Yakovleva, Natalia, Joseph Sarkis, and Thomas Sloan. 2012. "Sustainable Benchmarking of Supply Chains: The Case of the Food Industry." *International Journal of Production Research* 50 (5): 1297–1317. doi:10.1080/00207543.2011.571926.

Yu, Yugang, Ganquan Huang, and Xiaolong Guo. 2020. "Financing Strategy Analysis for a Multi-Sided Platform with Blockchain Technology." *International Journal of Production Research*, 1–20. doi:10.1080/00207543.2020.1766718.**[Q10]**

Yu, Guodong, Fei Li, and Yu Yang. 2017. "Robust Supply Chain Networks Design and Ambiguous Risk Preferences." *International Journal of Production Research* 55 (4): 1168–1182. doi:10.1080/00207543.2016.1232499.

Zahraee, S. M., M. Khalaji Assadi, and R. Saidur. 2016. "Application of Artificial Intelligence Methods for Hybrid Energy System Optimization." *Renewable and Sustainable Energy Reviews* 66: 617–630. doi:10.1016/j.rser.2016.08.028.

Zhan, Jizhou, Shuting Li, and Xiangfeng Chen. 2018. "The Impact of Financing Mechanism on Supply Chain Sustainability and Efficiency." *Journal of Cleaner Production* 205: 407–418. doi:10.1016/j.jclepro.2018.08.347.

Zhao, Lima, and Arnd Huchzermeier. 2015. "Operations–Finance Interface Models: A Literature Review and Framework." *European Journal of Operational Research* 244 (3): 905–917.

Attachment Files

1 Figure 2.doc *: Figure 2. Integrated meta-framework*