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Olan, F

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Sustainable Supply Chain Finance and Supply Networks: The Role of Artificial Intelligence

F Olan[1], Emmanuel O Arakpogun [1], U Jayawickrama[2], J Suklan [1], and S Liu[3]

[1] Northmberia University, Newcastle, UK

[2] Loughborough University, Loughborough, UK

[3] Plymouth University, Plymouth, UK

Abstract
Supply chain finance (SCF) is receiving increasing awareness in research as a result of uncertainties in the global financing for supply chain (SC). There are limited and fragmented studies in the implementations of financial services in SC management. This article builds on recovery from the financial crisis of 2008 and posts COVID-19 pandemic, where uncertainties crippled SCF providers and brokers services. At the same time, cutting-edge technological advancements such as Artificial Intelligence (AI) are revolutionizing the processes of business ecosystem in which SCF is entrenched. This article thus adopts a fuzzy set theoretical approach to unpack the entities relationship validity for sustainable SCF mate-framework, and the originality of AI concepts to sustainable SCF to identify the issues and inefficiencies. The results indicate that AI contributes significant economic opportunities and deliver the most effective utilization of the supply networks. In addition, the article provides a theoretical contribution to financing in SC and broadens the managerial implications in improving performance.

Keywords: Artificial Intelligence (AI), supply chain (SC), SC finance (SCF), SC network.

I. INTRODUCTION

In the last two decades, technological advancements in supply chain (SC), underpinned by computerized shipping and tracking, enterprise resource planning (ERP) and big data, are still emerging with innovations contributing not only to human intelligence, data analytics, and system thinking but efficiency of SC management. In particular, the potentials of SC networks as assets for SC companies, combining technologies and systems applications to the SC modules. However, the application of Artificial Intelligence (AI) technologies in SC is rather too slow or limited while the distribution of enterprise environments is at a higher stage of implementation in their operations [1].

Conventionally, SC finance (SCF) focuses mainly on financial aspects of SC management, particularly defining inventories as cash flows in view of an application for financial services in this sector of global business [2]. Furthermore, AI is one of the enablers of global financing in business services, hence the role of AI in building a relationship between SCF and SC networks [3]–[5]. The introduction of AI technologies, according to Du *et al.* [6] primarily reduces SCF and SCN challenges such as lack of consideration of operations assets available in supply networks during application for financing limits the capacity of SCN. Nevertheless, with the emerging opportunities through AI enabled SCN, sustainable financial services can be implemented [4], [7]–[10] Thus, SC operations exist in multiple environments categorized by technology, organizational culture, and systems that vary depending on the policies in the region where they operate [11]. Therefore, in terms of major challenges that exist in the SCF and SC networks environments, such as increasing regulations imposed by financial providers, AI can provide pathways to overcome these barriers by analyzing information and data flow and providing alternatives in SC operations. In addition, SCF has become the hub for processing global SC financial services in this age of digital transformation. Global markets and SC operations now face the challenges of developing innovations and technologies to integrate SC networks with financial services.

Past SCF studies have examined the impact of the last economic recession on financing in SC, they proposed interorganizational management of financial flows and the advantages of infrastructure sharing as working models for SC [12], [13]. Most of the previous work focused on interorganizational SCF however SC networks and technological advancements such as AI have very limited considerations, as SC networks continue to grow, leveraging technology-driven financing methods such as procure-to-pay, which integrate both financing functionalities and purchase management systems are becoming prefer alternatives for SC financing [14]. Furthermore, large financial brokers and institutions are supporting these emerging initiatives worldwide, AI systems from current studies are projected as the tool to advance the course of financing in the SC

management post COVID-19 pandemic, offering more reliable partnerships between the financier and the SC companies [15]. Furthermore, SC networks act as a single colossal system of interconnecting SC companies and financial institutions/brokers, providing a link to control and manage financial services, tracking, and cash flows. Nevertheless, gaining continuous access to the supplier's networks requires direct relationships with companies' operations, and a higher level of SC integrations, which also has a direct impact on the independence of an individual supplier's security. The role of AI as a technological tool is to bridge and stimulate SC financing through existing SC networks, minimizing complications experienced by valuable SC companies as a result of tougher financing application requirements, understanding the designs and operations of SC networks [4], [5], [16], [17]. Thus, this article investigates the theoretical research on SCF, SC networks, and AI in SC management, which leads to two primary research questions:
RQ1: What are the components of SCF and SC networks that are required for an AI system?
RQ2: Can AI simplify SC financing by understanding the relationship between SCF and SC networks?

To achieve the objectives in this article, a fuzzy set theoretical approach for complimentary and equifinality of entities relationship as proposed in the conceptual meta-framework because it can evaluate consistency and coverage threshold among the criteria. This article responds to the need for theoretical insights to SC financing and the importance of SC networks. This article first explores the theoretical background, then presents an in-depth study, data analysis, and the findings. Finally, the article concludes with a discussion of the implications of this article for research and practice, limitations, and future research directions.

II. THEORETICAL BACKGROUND

Sustainable SC financing as a continuous process tackles the challenges posed since the 2008 economic recession and post COVID-19 pandemic by holistically connecting financial institutions and brokers with SC companies, past studies argued for collaborative resources sharing, financing models and government grants for SC sector. As prior studies examined single factors of SCF risks [18], SCF opportunities [19], and SC firms [7], this section provides an in-depth review of SCF, SC networks, and AI with a perspective on a conceptual meta framework.

A. Sustainable SC Finance

According to past studies, there is a common phenomenon in SC that information, products, and financial flows are relevant factors in theories and to practitioners in understanding how to improve financing across SC companies [12]. According to Caniato *et al.* [20], SC companies consist of entities that operate in SC management which include suppliers, transportations, retailers, etc. Based on this understanding, considerable efforts were devoted to studying product mobility and data flows [21]. However, this does not apply to financial flows, where advanced optimization around product mobility and data flows is not up to date in terms of the integration of SC operations and financing. In general, a new stream of literature is emerging on some related topics to bridge this gap in the research.

In this age of digitalization, SC companies are facing enormous pressure regarding the operations of their business activities and processes, providing the best service without disruptions and meeting the needs of their customers [22]. The evolving innovation in information technology provides a new paradigm for SC operations, and some challenges for SC companies are becoming manageable [7]. Nevertheless, the recent financial crisis and COVID-19 pandemic led to various difficulties for SC companies, customers' demand has skyrocketed with a limited turnaround time, creating the need for SC companies to seek more financial resources to meet the ever-growing demand in the market [23]. Tactlessly, with the last financial crisis, financial institutions and brokers raised the standards and requirements for financing applications [12], making it extremely difficult to access financing for companies with inadequate cash flows.

Furthermore, to meet the level of demand, SC companies require consistent and stable cash flows for sustainable and efficient daily operations. Carnovale *et al.* [24] argued that SCF driven by technology is an innovative method that solves the problems of financing for SC companies by considering cash flows and other activities in their operations. In addition, Lam Hugo [18] further explains the principle of SCF as a fundamentally integral component of financing in SC processes, financial institutions and brokers provide some credit and trade financial services to facilitate and support SC companies' operations, another study [25] argued that SCF as a financing solution for SC provides alternative solutions for credit issues improving SC companies performance by working in partnership with other companies and leveraging joint resources to reduce the risks of interruptions while supporting financing and operations opportunities in SCs.

Hence, SC financing can take advantage of the commercial finance environment by combining technological advancement and financial solutions into a single system for financial and operational integration. Osadchiy *et* *al.* [26] argued that SC financing, such as business-2-business (B2B) also known as trade credit and crowdfunding, in practical terms, are expanding as their customer networks growat an exponential rate. Nonetheless, the challenge of cash flow deficiency remains as SC companies' financial and operational problems. Hence, exploring technological innovations for SC financing is not just important for research, also SC cash flows as SC companies are constantly seeking ventures from multiple sources from the financial capital market and stakeholders to sustain their operations and improve their partnerships [27].

As SCF is the most important financing solution for most SC companies that are struggling with access to steady and readily available cash flow, Zhao and Huchzermeier [28] further categorize SCF into collateral SCF, time-based SCF, and credit SCF. According to financial economics theory, SC companies have the ability to achieve specific organizational goals and excel when there is a financial mechanism in place to support their goals and objectives [29]. Lekkakos Spyridon and Serrano [25] provided a detailed outline of the role of financial institutions and brokers in granting financial facilities to SC companies by managing the information asymmetry in cash flows.

B. SC Networks

SC networks represent the new integrative innovation in the SC financing processes for SC partnerships working towards a beneficial pool of resources and improving products and services, SC companies are investing in innovative processes, as their operations are directly linked with financial services [30]. In SC management context, the environment is fundamental for SC networks, most especially when SC companies interlink both their associated suppliers and customers [31], [32]. Consequently, the relationships among partners (SC companies, suppliers, and customers) in the definition of the overall structure for a sustainable SC networks, assuming the significant integration of new structures with existing interconnections. Scholars discussed how SC management studies are continuing to improve SC networks theory and helping to tackle SC challenges [33].

The need to establish sustainable SC networks for SC financing led to the search for more knowledge through research on SC networks-based theories and applications. Studies on SC networks explored SC procurement and sourcing networks and found that they can have a positive effect on SC suppliers and customers responsiveness [34], [35]. Building on the fundamental research output showing the history of SC networks' structure and development, there are opportunities to construct SCF networks and future advancements in SC networks, these new opportunities, such as sustainable financing depends on innovations. Hence, SC networks-based theories proposed new network perspectives that revealed innovative network structures and compositions in global SC financing [36], [37]. Prior studies showed significant connections between SC networks structures and SC companies' operations implementation, following a similar line of inquiry presented by the role of network brokerage [38]. Specifically, SC companies have the ability to expand SC networks structure globally when network features grow with advancing technologies and information flows, the important role of SC companies positions in the operations of networks is that it can increase the company's governing and negotiating power and facilitate financing through financial institutions and brokers [39].

SC companies that maintain a consistent, reliable, and operational set of activities within the SC networks experience momentous advantages and benefits in obtaining resources, such as funding through crowdsourcing [40]. Predominantly, from the view of resource dependency theory, SC companies struggle to operate autonomously, as they require networks to accommodate the interdependencies in product and service flows, resource flows, and information flows [41]. These dependencies in SC markets create opportunities for SC companies to use the links to make considerable commitments in building sustainable technology driven SC networks. Some studies indicated that the interdependencies can either positively or negatively affect SC operations, and highlighted opportunities for further research [42]. According to Pfeffer and Salancik [43], interdependence is a continuous process in which SC companies can foster inter-corporation based on resource and information sharing. However, further studies demonstrated that the degree of interdependence is also a risk in resource dependency theory, so putting mitigating parameters in place to address disconnections within the network is an important condition. Basole *et al.* [31] discussed that as SC networks is a global emerging field, risk management and business continuity packages are rolled out simultaneously. Therefore, the initial concerns raised [26] are considered in global SC networks.

SC companies are taking advantage of the SC structure, practices, and resources in a single network, however with multi-layered hosts in the SC management databases, particularly SC financial institutions and brokers. The extensive research on SC management supports this concept, suggesting that SC companies are competent at managing high levels of operational and risk controls, including the ability to forecast SC echometric trends [44]. Furthermore, recent research showed that the direct financial outcomes associated with SC networks, such as cost saving, result from networks sharing brings together SC companies and customers in a technologically driven platform [45]. Certainly, this article [31] found that in purchasing, there is increasing support for SC networks in implementing resource management and distribution at the early stage. In addition, it is significant to understand whether or not there are benefits for SC companies that operate in a shared global SC network. However, few studies showed that there are strategic performance rewards, such as financial benefits, in a single multi-layered SC networks that connects SC companies in a unified technology driven resource system [33], [36], [39].

C. Artificial Intelligence in SCs

SC management is encountering complex supply financial challenges, such as cash flow shortages and tougher access to financial credits. SC success is rooted in the company's ability to innovate, implement, and operate new ideas that benefit the entire SC networks with end-to-end SC operations and information flows [46]. Thus, the introduction of AI to SCF and SC networks support technological advancements in SC management, such as technology driven materials acquisitions, digitalized cash flows systems, and automated networks to meet customer demand [47], [48]. The significance of digitization in SC management is that it enhances end-to-end SC operations and processes. Cutting-edge SC innovations can create the foundation for implementing AI and gaining the benefits of enriched data analytics tools consisting of intelligent networks and systems [49], [50]. SC financing is becoming more data driven and focuses on alternative asset evaluations in which inventory, equipment, and warehouses become real substitute data [51], [52]. In addition, increasing significance of information in SC management, SC researchers and experts must continue to explore the benefits and challenges of managing large amounts of information [53], [54]. According to Martínez-López and Casillas [51], AI has existed for decades, though it has not reached its full potential, especially for the SC management sector of the global economy.

However, it is worth noting that cyber risks such as cyberattacks, malicious spying, and tempering are common to technology advancements, such as AI, most of these cyber risks are invisible to detect in SC [55]. According to studies carried out by Radanliev *et al.* [56], cyber systems such as AI technologies are transactional environment for exchange of valuable information on products and services, the safeguarding of interactions and information in essence is significant to SC companies. Furthermore, technology advancements, such as AI, big data, and the internet of things are continuously investing in the security of data and developing new methods of shielding companies' valuable information from cyber risks and increasing confidence in AI technologies.

1) *Artificial Intelligence Networks:* The theory of artificial neural networks (ANNs) was developed to reflect the human brain, which uses the analogy of brain cells (neurons) in the design [57], [58]. Building on this concept, AI networks are connected like human memories and have the ability to learn and improve over time, which characterize its experience, distinct features, and complex analysis processes [59]. ANNs consist of several nodes that represent human neurons [60] with multiple links connecting these nodes, where each link has a set of algorithms programmed into it for efficiency and to process complex commands. Furthermore, these links connecting the nodes have weights that are the core for long-term memory storage, data processing, and data analytics. AI networks process data with systemic methods where the output of one neuron is transformed into the input for another, making every single process a prerequisite for a new process [61]. According to Russell and Norvig [58], one of the functions of the weights in AI networks is to determine the strength or weakness of data passing through the links. The links provide an environment that hosts the values of the combined weights to form an AI process for learning. AI networks learning capabilities create an opportunity for deployment in the SC management sector, specifically by integrating SCF,SCcompanies, and suppliers' data, and creating patterns for interrelationships among data [62]. At the initialization of the AI networks, the system continues to improve its intelligence and performance with built-in learning algorithms by understanding SC operations and analyzing the optimum efficiency and required resources.
2) *Artificial Intelligence Systems:* AI systems are technologically driven systems with the ability to simulate human cognitive skills, such as analyzing complex problems, visual analytics, optimum performance, and providing solutions [63]. Cheung *et al.* [64] reported that AI systems have the capacity to perform analytic reasoning in complex problem-solving in contrast to human expertise problem-solving abilities. There are three fundamentals in AI systems: knowledge networks; interface engines; and user interfaces. Knowledge networks are the depository for data, facts, and rules of engagement during human activities, and are the basis for the resources that build AI systems [34], [37]. The interface engine is a collection of algorithms for problem-solving reasoning, which is also referred to as the brain of AI systems and is primarily responsible for conduction complex analyses, such as solution search, algorithm reasoning, and providing an interface for the knowledge networks to

leach on in an AI environment [65], [66], while the user interface connects the users with the system and supports user queries for interaction and communication [67]. Overwhelmingly, AI systems are designed with the concepts and operations for the domain in which they will be implemented. Thus, experts and practitioners who are knowledgeable about the tasks and role of the AI systems and human-system interaction will be practicable in problem solving [53], [68]. In particular, AI systems showed tremendous progress in terms of increasing performance in most sectors [69], such as manufacturing, specifically in the automobile industry. Tesla car manufacturing reached 75%automation of the entire production process, where AI systems were implemented and led to higher performance and less waste. The application of AI technologies and systems in SC management, specifically the integration of SC operations and financing, is emerging, as evidenced in the successes of AI implementation in logistics and manufacturing.

III. RESEARCH META-FRAMEWORK

This article developed a meta-framework based on the discussion of the theoretical background on three key perspectives: SCF; SC networks; and AI. These perspectives will be combined later in associations to find possible relationships. Table I gives how previous studies contributed to this article. To answer the research questions, this article will initially conceptualize the SCF [70], SC networks [31], and AI [71] perspectives.

TABLE I
THEORETICAL REVIEW SUMMARY

Citations (category order)	Research Context	Research aims	Benefit to SCF	Benefit to supply chain networks	Benefit to AI
[12, 72]	Supply Chain Finance	In-depth comprehensive literature review of studies on financial risk management, challenges, and opportunities	Building conceptual frameworks and models to enhance the understanding of SC financing.	Finding associations from the SCF literature to support the meta-framework in this research	Supports investigations of the relationships defined for attributes of SCF and supply chain networks
[34]	Supply Chain Networks	Understanding the operations of networks, the layers, and SC operations	Literature linking conceptual frameworks and models in SCF	Finding associations from the AI literature to support the meta-framework in this research	Supports investigations of the relationships defined for attributes in the SCF perspective
[52]	Artificial Intelligence	Technology strategies, models, and implementations incorporating new supply chain networks and operations	The holistic approach presented compares the traditional SCF processes with modern SCF processes, traditional SCF verification	Finding associations from the AI literature to support the meta-framework in this research	Supports investigations of the relationships defined for attributes from the SCF and supply chain networks perspectives
[73]	Fuzzy Set	A set theoretic technique designed for set theory analysis by creating patterns of attributes defined by numerous features and to generate outcomes on the construction of relationships	Complementarity and equifinality testing by generating consistency and solution coverage	The combination system supports the relationships in the supply chain networks and AI perspectives	A holistic approach targeting new attributes in three constructs mapped to establish relationships for data collection, theory testing, and producing outcomes

Note: Table I gives the underpinning literature that contributed to the four-research focus (SC finance, SC networks, artificial intelligence, and fuzzy set).

A. SCF Perspective

While prior studies provided many different descriptions of SCF, as they commonly state that the purpose is to provide cash flows for SC companies [12], [13]. Therefore, this article identified three components in this perspective: financial orientation (FO); SC orientation (SCO); and (3) cash flows (CF). The FO of the SCF perspective consists of a set of innovative solutions that financial institutions and brokers can rely on when making decisions when assessing applications by SC companies and suppliers, as they are the controlling actor in the SCF decision-making process. FO focuses on financing solutions that are important for payables or receivables and that are viable for the benefits of both the financial provider and SC companies and partners [74]. Thus, FO is a significant trigger in the SCF perspective, with the main objective of supporting sustainable SC operations.

The SCO component in the SCF perspective manages the records in the inventories, such as the optimization of customer and supplier inventories, thus ensuring sustainable working capital to support daily SC operations in ensuring that market demands are met [75]. In addition, SC companies and their partners prioritize effective control and monitoring of financing and working capital, as shown in Fig. 1. The SCO ensures sustainable availability of working capital or financing at the lowest rate to maintain SC operations.

Cash flow (CF) is a vital resource for daily operations that support the company’s activities and keep the business afloat [36]. In addition, CF demonstrates SC operations performance and indicates the direction in which cash is applied, allowing decision-makers to implement sustainable CF for SC operations, as this is an important factor when seeking financing from financial institutions or brokers.

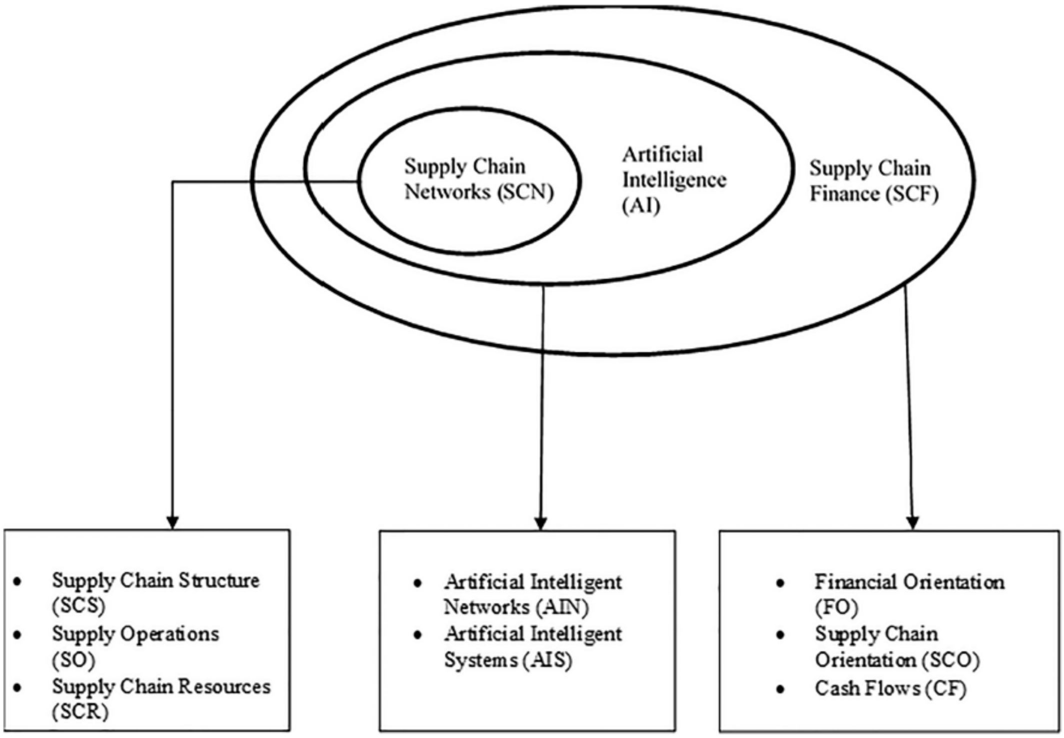

Fig. 1. SCF meta-framework. Note: Fig. 1 is the derived SCF meta-framework indicating components of the three-research focus (SC finance, SC networks, and AI) and components derived.

B. SC Networks and AI Perspectives

As shown in Fig. 1, the SC networks, and AI perspectives combine to design sustainable networks consisting of strategic entities that integrate the SC associations of the members to create SC networks built on AI. There are three components associated with the SC networks perspective and two components associated with the AI perspective. According to Martinez *et al.* [8], traditional SC networks are studied with a focus on understanding the existing connections to SC operations, leading to the strategic development of possible blockchain integration through existing channels. With this understanding, this article proposes an advanced SC networks implementation driven by AI technologies. It is already known that SC networks support innovative technology in SC management areas such as SC operations. However, there are emerging opportunities to develop sustainable SC networks for SC financing driven by AI technologies. Fig. 1 shows that the AI-related components are embedded in the existing SC networks, indicating that existing information flows in the network are seamlessly transferred to AI knowledge networks for intelligence analysis.

IV. RESEARCH METHOD

A. Research Design and Data Collection

Following the design method [15], this article used a longitudinal survey with online participants to test the relationships and associations in the proposed meta-framework. A cross-sectional online survey was conducted in 2019, we selected active participants through research conferences, SC specific events, and use online platforms, such as LinkedIn to engage in the survey exercise. This survey is for members, employees, and managers in SC organizations across the globe. Participants were also drawn from SC associated organizations, such as technology for operations management. The questionnaire was developed through the research gaps identified from SCF, SC networks, and AI literature, the associations identified in Fig. 1 transformed into sections of the survey.

Consequently, we distributed the survey to 3185 active targeted participants and received 432 surveys that included both partial and completed participations. This accounts for a response rate of 13%, a study response rate that is consistent with extant research [76]. Since this article is unable to select partially completed surveys for analysis, our final sample number thus only consists of 205 completed surveys. This article sample size consists of participants from across the globe, with North America accounting for 29% of the total survey which makes up for the largest share in terms of participant size. Experience with SCF platforms shows that 28% of the participants engage more than five times daily on the SCF platforms while 22.7% account for participants with five to six years working the SCF platforms. The research design was developed using this method, and the online survey was conducted using stratified sampling and the participants were proficient professionals in SC operations consistent with SC financing and have experience working with AI technologies. The participants were divided into specific demographic groups. Table II gives the expert profiles consist of gender, age, work locations, SCF/SC networks/AI usage, and SCF/SC networks/AI experience.

TABLE II
EXPERT PROFILES

	No.	Percent		No.	Percent
Sex			SCF Platform Usage		
Male	149	72.3	Once a week	2	1.0
Female	57	27.7	2–4 times a week	4	2.1
			5–6 times a week	11	5.2
Age			Once a day	33	15.8
18–24	15	7.2	2–3 times a day	47	22.9
25–34	33	15.9	4–5 times a day	51	24.6
35–44	53	25.5	More than 5 times a day	59	28.4
45–54	63	30.8			
55–64	39	19.1	SCF Platform experience		
65 or above	3	1.5	Less than a year	15	7.6
			1–2 year(s)	22	10.5
Location			3–4 years	37	18.2
Africa	26	12.5	5–6 years	47	22.7
Asia	36	17.5	7–8 years	46	22.3
Australia plus Oceania	26	12.7	9–10 years	22	10.6
Europe	53	25.8	More than 10 years	17	8.1
North America	61	29.4			
South America	4	2.1			

Note: Table II gives the breakdown of the participants in the carried out underpinning literature that contribute to the study. The participants were sourced across the globe to ensure that the data analysis generates results that represent a world perspective.

B. Data Variables

We obtained both dependent and independent variables using a multiple item, ranging from 1 symbolize “strongly disagree” to five representing “strongly agree” on the five-point Likert-type scales. The use of five-point Likert-type scales ensures that the survey responses conform to statistical variability, due to difficulties in proof objective data relationship outcomes as shown in past studies [77], [78]. therefore, as prior studies created a composite scale to capture relational and scalable dimensions of supply relationship, this article follows a similar approach on the scale return to represent what we intend to measure.

C. Non Response Bias

Nonresponse is a frequently applied technique for assessing the bias in a research method, this article suggests that the participants that responded to the survey in the first month were at a 75% rate while 25% responses were completed later in the study variables. One-way nonresponse bias, performed at the entry-level suggests that there are no significant differences between the data gathered from an earlier stage and later responses, only that 1 in 26 which is 1.73% of the study variable. Concluding that nonresponse bias exists at the beginning of the time of participation is due to chance.

D. Common Method Variance

To minimize the impact of common method bias linked with reporting data sourced from one point such as survey, taking precautions in gathering the data, we followed guided procedures as suggested by Kave [79]. The initial step taken in this article is to foremost ensure that most of the participants have experience working in the

SC industries and are familiar with the technological platforms used in the sector. Most of the participants that responded to the survey have at least three years of work experience in the SC industries with sufficient managerial roles and knowledge about the increasing use of technology in the sector. Participants in the survey were reassured of the diligence ethical process in keeping their data anonymous. The inclusion of additional independent variables tends to reduce common method variance, the questions were organized in a strategic method to include intersperse entities.

E. Analytical Technique

According to Oyemomi *et al.* [80] and Chen *et al.* [81], a fuzzy set is a set-theoretic approach that evaluates theories, frameworks, and models with a deductive strategy driven by a positivist paradigm. Fuzzy sets are not a new technique for pure sciences and engineering, but are an emerging method in the management and social sciences, as researchers without a science and engineering background encounter problems, such as approximate reasoning. However, the introduction of hybrid analytic techniques with fuzzy set logic that support fuzzy analyses in management and social sciences addressed these initial problems [82]. This article adopted relationship and association testing, as suggested in earlier work to test for Boolean expressions in the fuzzy set-theoretic approach for the four intersections in Fig. 2.

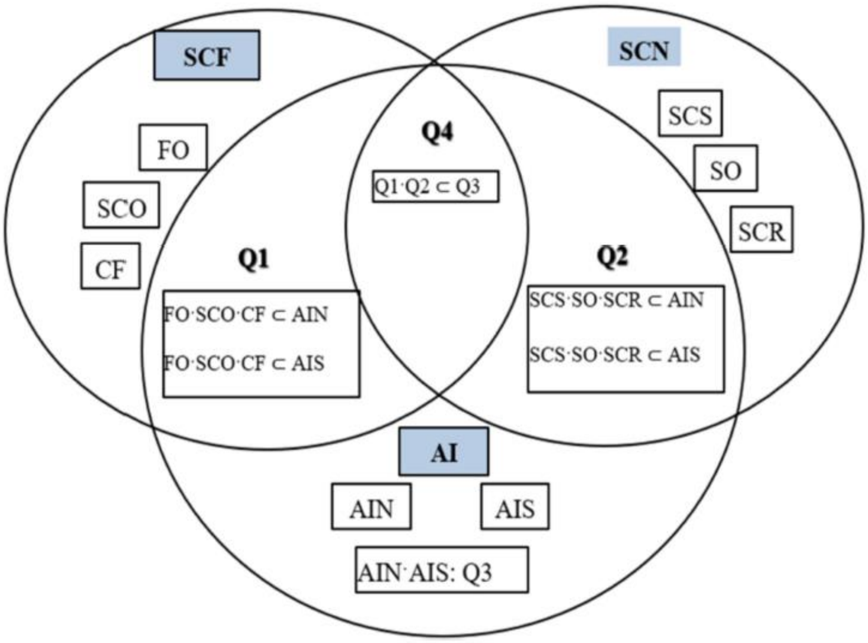

Fig. 2. Integrated meta-framework. Note: $Q1$ = Association one SCF = SC finance; SCN = SC networks; $Q2$ = Association two; FO = Financial orientation; SCS = SC structure; $Q3$ = Association three; SCO = SC orientation; SO = Supply operations; $Q4$ = Association; Four CF = Cash Flows; SCR = SC resources; AI = Artificial intelligence; AI = Artificial intelligent systems; AIN = Artificial intelligent networks. (a) Financial orientation. (b) SC orientation. (c) Cash flows.

This article proposes an eight-step process flowchart (see Fig. 3). It consists of four loop relationships (represented in a double-line diamond) and three straw-in-the-wind relationships (represented in a single-line diamond) and shows the subsequent relationships used to discuss the outcomes from the analysis [76], [83], [84]. The flowchart is described as follows.

1) A loop relationship for an expression that a solution pathway is reliable shows whether the consistency of the sufficiency analysis is greater than 0.7 of the solution pathways as defined in this article for the consistency threshold analysis. Any relationship that falls below the set threshold is eliminated from further analysis testing as this means that that relationship does not meet the acceptable reliability. A loop relationship for an expression with an accepted solution pathway shows whether the consistency of $Q1$ is greater than 0.7, suggesting that any relationship that falls below the acceptance criteria in the solution pathway must be rejected and there should be no further analysis.
2) A double-line diamond relationship for an expression that is strongly supported shows whether the consistency of $Q2$, $Q3$, and $Q4$ is less than or equal to 0.7, suggesting that any relationship that passes the acceptance criteria does not have significant contradictory proofs.
3) A single-line diamond relationship for an expression that is not supported by itself, though would benefit subsequent relationships, can be described by the consistency of $Q3$ of less than or equal to 0.7. Furthermore, $Q3$ represents the type I consistency error, which usually has a lower acceptance threshold.

4) A loop relationship for an expression for which a solution pathway is weakly supported shows whether the consistency for the sufficiency analysis result that $Q1$ is greater than $Q3$ in the solution pathways as defined for the consistency threshold analysis. Any relationship that falls below the set threshold is eliminated from further analysis testing, as the relationship does not meet the acceptable reliability.
5) A double-line diamond relationship for a supported expression shows whether the consistency of $Q4$ is less than or equal to 0.7, suggesting that any relationship that passes the acceptance criteria does not have a significant error reported during the analysis and supports the classification.
6) A loop relationship for an expression for which a solution pathway is not weakly supported shows whether the consistency of $Q2$ is greater than 0.7, suggesting that any relationship that falls below the acceptance criteria in the solution pathway can be improved and there is weak support for the classification.
7) A double-line diamond relationship for a supported expression shows whether the consistency of $Q2$ is greater than or equal to $Q4$, suggesting that any relationship that passes the acceptance criteria and partially supports the condition for $Q2$ and $Q4$ represents the type II consistency error, and it is usually equal to or higher than the acceptance threshold.

F. Data Analysis and Results

According to [83], complementarity and equifinality are two underlying features in the fuzzy set theoretic approach. It displays patterns of attributes and different results depending on the structure of the perspectives. The attributes in the perspectives are concerned with the present or absent conditions and the associations formed during conceptualization, rather than isolating the attributes from the perspectives. Furthermore, complementarity does exist if there is proof that causal factors show a match in their attributes and the results indicate a higher level, while equifinality exists if at least two unidentical pathways known as causal factors show the same level of results [85].

The results in Table III for the different perspectives indicate the part of the relationships that show empirical evidence for rejection and support. The results demonstrate that the relationships are more likely to yield rejection than support from this analysis. The solution pathway shows in the results, confirming the relationships. Consequently, supporting prior findings [86], [87], Fig. 3 illustrates that a higher consistency level value directly results in a higher reliability of the relationship. The three combinations of attributes in the sufficiency analysis shows that the input efficiency either fails or passes the set consistency threshold requirement (consistency and coverage are 0.72 and 0.44, respectively).

In Table IV, the relationships indicate support that the analysis generates attributes in the perspectives above the combined solution pathways than in Table IV. As shown, the type II error of a false negative is one form of contradiction between the relationships and results which is ignored, as defined in Fig. 3. These findings indicate the least likely attributes in the perspectives show that the existing relationships hold, supporting the higher consistency level of the associations and stronger support for further relationships. Hence, this analysis can introduce additional causal conditions of similar attributes not yet shown in the current relationships by tracking back to the relationship mapping data, thus finding common attributes in the existing perspectives that may explain the undefined variance from the existing relationships.

The results in Table V for the combined solution pathway for consistency and coverage indicate support for most attributes in the perspectives, indicating a type I error (or a false positive) in the form of contradicting variances in the relationships. In addition, the higher consistency level of the associations supports higher values to delimit the relationships. Thus, some unconfirmed attributes indicate a restriction of the current relationships.

The analysis in Table VI of the combined solution pathway indicates that neither prediction in the relationships nor coverage by attributes definitions for the perspectives are strongly supported in the SCF for the role of AI technologies in SC networks. Therefore, alternative variances, as understood by experts and researchers, provide better supporting conditions for the definitions of the relationships in Q4. Five out of the six pathways are equal to or greater than the defined threshold, indicating that the relationships between the perspectives can benefit from tradeoffs. Furthermore, there are similarities in the results for the unique coverage, signaling significantly high efficiency input linked directly with the variance from the causal conditions.

outcomes from $Q1$, $Q2$, and $Q3$ simultaneously. $Q1$ and $Q2$ alone are not adequate to support high input efficiency, indicating that AI will fade-out without a correlation with SC networks. Therefore, the combination of the two perspectives is highly significant to the relationships to create high input efficiency. However, $Q3$, which considers all attributes in the AI perspectives, rejects the associated attributes from $Q1$, but shows weak support for $A2$, indicating that the conditions are peripheral or are conditions with less supporting variance. This explains the weak support in the attributes of their relationships. *Q*4 outcomes show that this article considers the relationships of the attributes of the relations between *Q*1 and *Q*2, as the roles of *Q*3 have explanatory control over the outcomes from redefining the impact of both associations.

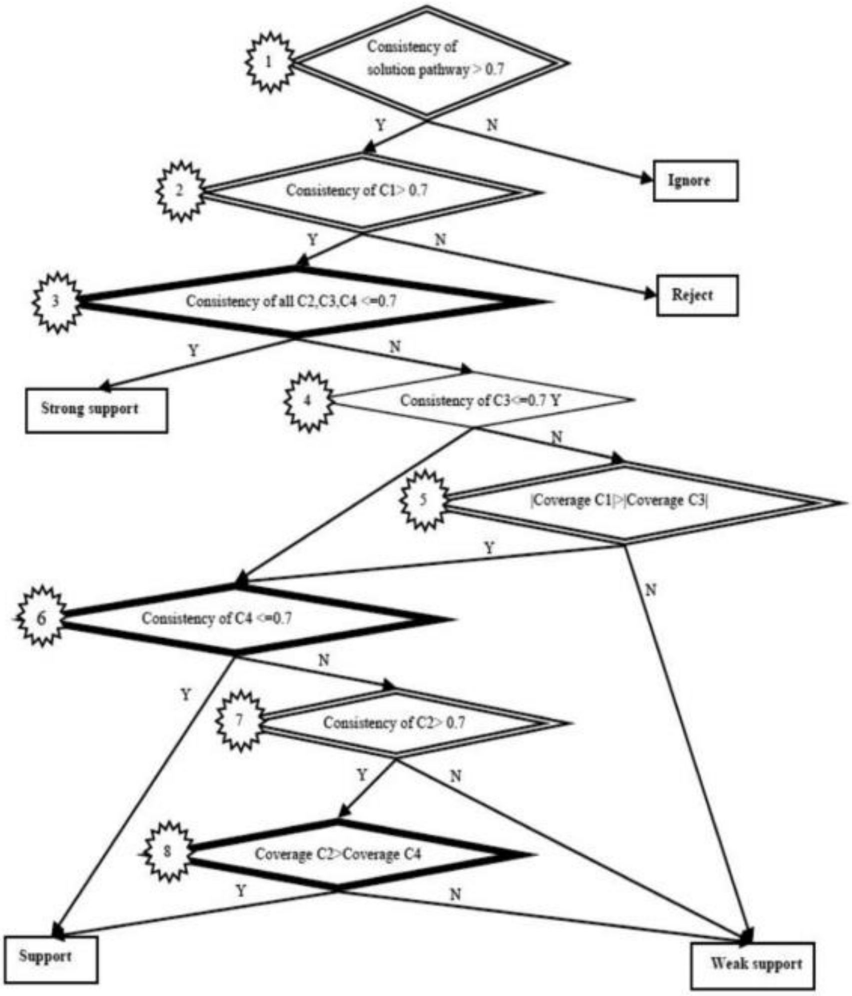

Fig. 3. Flow chart: fsQCA Analysis. Note: where cut-off consistency greater than 0.7 proceed to next stage consistency threshold, where preceding coverage greater than later, there is weak support.

This article developed a meta-framework for the role of AI in building sustainable SC financing using SC networks that are currently operating in SC activities by exploring novel findings that individually or in combination established links to build on for the three perspectives. An online survey was carried out with a stratified sample to test the meta-framework, and the data were used to further categorize the relationships among the perspectives. The empirical analysis shows important results that further the understanding of these associations.

The findings show that Table III results for *Q*1: FO_SCO_CF/AIN/AIS where the relationships of both AI and SCF constructs in the solution pathway result are supported. Cheung *et al.* [64], highlight the significant role of AI in aiding innovative organizational operability and providing sustainable competitive advantages. As findings in Table IV, results for *Q*2:SCS_SO_SCR/AIN/AIS demonstrate support for constructs associations. More specifically, a section of Table IV, *Q*2: SCS_SO_SCR/AIN (S2) indicates that there is strong support for implementing AI networks with existing SC networks. AI technologies were implemented, there has been significant improvement to the operations and processes, complex tasks are simplified using AI algorithms.

TABLE III
RESULTS FOR Q1: ARTIFICIAL INTELLIGENCE AND SC FINANCE

	Q1: FO·SCO·CF/AIN					Q1: FO·SCO·CF/AIS	
Condition	S1	S2	S3	S4	S5	S1	S2
Consistency	0.698892	0.692181	**0.740252**	**0.733449**	**0.785004**	**0.970090**	**0.712693**
Raw coverage	0.236909	0.566492	0.164245	0.167030	0.091458	0.027005	0.445208
Unique coverage	0.048374	0.336715	0.002648	0.005320	0.031859	0.010598	0.428800
Solution consistency	0.686555					**0.716547**	
Solution coverage	0.665239					0.455806	
C1: H•S⊂Y-Consistency	**0.75716**	**0.812902**	**0.827317**	**0.827317**	**0.988559**	**0.991696**	**0.916804**
C1: H•S⊂Y -Raw coverage	0.085357	0.067400	0.034448	0.034448	0.008089	0.006429	0.054261
C2: ~H•S⊂Y -Consistency	0.689295	0.692412	***0.739000***	***0.731484***	***0.786105***	***0.959823***	***0.711222***
C2: ~H•S⊂Y -Raw coverage	0.191634	0.565667	0.163395	0.166122	0.092622	0.027701	0.435212
C3: H•~S⊂~Y - Consistency	0.600079	0.466213	0.466213	0.466213	0.466213	0.548037	0.577609
C3: H•~S⊂~Y -Raw coverage	0.058389	0.074411	0.074411	0.074411	0.074411	0.076858	0.074661
C4: ~H•~S⊂Y -Consistency	0.535569	0.476600	0.532806	0.534341	0.512781	0.446069	0.388852
C4: ~H•~S⊂Y -Raw coverage	0.841081	0.505483	0.860575	0.859848	0.864034	0.910765	0.582426
Solution pathway result	Ignore	Ignore	Support	Support	Support	Support	Support
Combined solution unique pathway Coverage of result			0.039827			0.439398	
Overall pathway result	**Support**					**Support**	

Note: $S1$ = Solution One
$S2$ = Solution Two
$S3$ = Solution Three
$S4$ = Solution Four
$S5$ = Solution Five

V. DISCUSSION

The findings in this article demonstrate the important role of AI as shown in the associations of the construct with SCF and SC networks, the introduction of AI in practice as a tacit control of the SC networks as a resource for secure access to financial resources, and unavoidably includes other resources that benefit the SC. Consequently, AI puts together SC networks with SCF criteria set by the financial institutions and brokers, suggesting two themes. First, ensure that the dependence controls are balanced and that access to resources is mutually beneficial to all parties by consistent monitoring of performance. Second, network system homogeneities, structure and operations become a unified network that identifies resources usage and efficiency. The purpose of this article was to find out the role of AI as a technology tool for stimulating SC financing through existing SC networks. Explicitly, we carried out a complimentary analysis to explore the role of an AI-enabled SCN in facilitating sustainable SC financing for SC companies. Three perspectives: SC finance; SC networks; and AI were developed following the development of SCF meta-framework, four intersections: $Q1$ = association one; $Q2$ = association two; $Q3$ = association three; and $Q4$ = association four between the three perspectives were further developed.

The outcomes gathered after analysis of validated data from questionnaire show that AI-enabled SCN is important in minimizing the issue of financing which limited assets available in supply networks. Consequently, the complementarity of the three perspectives; SCF, SCN, and AI technology further enhanced into four intersections relationship mapping by constructing entities association from each perspective as shown in Fig. 2. The results from Table III, suggest that the testing of the relationship of AI and SCF perspectives and their entities financial orientation, SC orientation, and cash flows of SCF and AI networks and artificial intelligent systems of AI are supported. Furthermore, the outcomes in Table III concur with the fuzzy set relationship mapping which discussed the consistency and coverage requirement in Fig. 3, suggesting that the implementation of AI technology to SC financing provides vital information on how the distribution of financial services can influence performance in SC. This result demonstrates consistent with the findings of [15] which discussed the significant role of AI in financing the food and drink industry. Hence, the relationship between AI and SCF perspectives illustrates support in the implementation of AI-enabled solutions to the financial services available in SC.

TABLE V
RESULTS FOR *Q*3: SIGNIFICANT ROLES OF ARTIFICIAL INTELLIGENCE

	Q3: Q1-AIN/AIS	**Q3: Q2-AIN/AIS**	
Condition	S1	S1	S2
Consistency	**0.710821**	**0.765686**	**0.765449**
Raw coverage	0.161335	0.271478	0.276201
Unique coverage	0.161335	0.005228	0.009951
Solution consistency	**0.710821**	**0.768799**	
Solution coverage	0.161335	0.281429	
C1: H•S⊂Y-Consistency	0.691323	**0.759535**	**0.759724**
C1: H•S⊂Y -Raw coverage	0.087053	0.187811	0.188006
C2: ~H•S⊂Y -Consistency	***0.707803***	***0.741407***	***0.742004***
C2: ~H•S⊂Y -Raw coverage	0.160089	0.175810	0.180727
C3: H•~S⊂~Y - Consistency	0.560523	0.623238	0.623238
C3: H•~S⊂~Y -Raw coverage	0.665845	0.640238	0.640238
C4: ~H•~S⊂Y -Consistency	0.597557	0.559862	0.556151
C4: ~H•~S⊂Y -Raw coverage	0.426468	0.417932	0.411692
Solution pathway result	Reject	Support	Support
Combined solution unique pathway Coverage of result	0.161335	0.015179	
Overall pathway result	**Reject**	**Support**	

Note: *S*1 = Solution One
*S*2 = Solution Two.

In Table IV, the result for AI and SC networks for their entities artificial intelligent networks, artificially intelligent systems, SC structure, SC resources and supply operations show strong support for the relationship as the consistency and coverage suggest that the association significantly influence the financial services for SC. The positive complimentary association further supports AI and SCN perspectives relationship mapping, with constructs' consistency and coverage meeting the set requirement in Fig. 3. Furthermore, there is support for the results Table V significant roles of AI and Table VI consistency in SC financing, except for the relationship mapping in Table VI for AI perspective entities artificial intelligent networks and artificial intelligent systems which shows a rejected relationship. The condition $S1$ is rejected as it is the only association that is tested with only one condition.

The findings strengthen the importance of the application of AI-enabled SCN to support SC financial services. In practice, AI-enabled SCN advances the understanding of challenges in financial services for SC, suggesting the exploration of the assets available through the SC [2], [15], [88], [89]. Other opportunities that are available with the SC networks include partnership in financial services, suppliers, financial service institutions, and SC industry benefits from AI driven financial services integrated into the network systems in the SC.

A. Implications for Research

This article proposed complementarity of SCF, SC networks, and AI technologies to understand the explanatory influence by linking theoretical views that did not consider these connections previously. This article used the perspective of complex causality to analyze the data and generate empirical findings. This article provided a new understanding of the proposed complementarity by contributing a holistic evaluation of all attributes of the three perspectives, building relationships, and presenting findings that identify the significance of each association in an effort to build sustainable SC financing using AI-driven SC networks. Therefore, this research builds on existing studies [9], [90] that call for further work on SCF and SC networks, while contributing to the role of AI by exploring the conditions under different scenarios and complementarity values. The online survey data supports the solution coverage across attribute dimensions by analyzing complementarity efficiency using defined threshold requirements. This article answers the call for enquiries into how SC networks (the environment) and SC companies can strategically allocate all resources for cascading SC financing. Most importantly, the fuzzy set theory technique accounts for complex causality to yield novel empirical findings.

This article contributes to the SCF, SC networks, and AI literature by developing a meta-framework that examines the integration of AI technology in existing SC networks, which can provide alternative SC financing by relying on the available resources and enabling financial institutions and brokers to partner with SC companies and suppliers through AI-enabled networks.

B. Implications for Practice

The comprehensive theoretical review and in-depth empirical analysis of the complex casualty on the role of AI in building sustainable SC networks for SC financing in this article allow SC companies and suppliers to consider their organizational strategies in their effort to create cascading networks and implement compatible sustainable solutions. As proposed in the relationships, the attributes from each perspective combinations demonstrate support for solution pathways in the outcomes, SC companies prioritizing innovative resources to ensure that AI-driven SC networks are sustainable assets for SC financing, as untapped potential resources are hiding with the layers in the networks in which SC operations are embedded. SC companies have long been searching for alternative sources of financing that consider current assets, such as operations and networks in SCF. With an innovative deployment of AI, financial institutions and brokers can support SC operations through AI technology, providing financial services based on transitions through AI-enabled networks. Therefore, financial risks are reduced, and AI-enabled networks can filter through complex and risk-exposed operations within SCs. The results reported here are important for financial opportunities for both short- and long-term sustainability on SC.

C. Limitations and Future Research Directions

Given the research aims and scope, this article has limitations that offer opportunities for future research. This article identified and analyzed SCF, SC networks, and AI technologies, focusing on sustainable SC financing through SC networks, though does not address other perspectives, such as SC companies' policies, political strategies, and negotiation strategies. Similarly, the sample during the data collection process targeted SC management experts and researchers, specifically those focusing on SC networks and financing, who engage most frequently in SC innovations by demography. However, financial analysts may be of relevance for future research. Given that previous research focuses on SCF risk management and financial challenges, to understand risks and issues in SC financing, the influence of AI as a possible sustainable solution to risks around SC financing will permit future research to proceed with new datasets. In the same line, this article did not consider the financial impact of implementing AI technologies, which is another interesting area for future research.

This cross-sectional research aimed to provide an in-depth understanding of the relationships among the three perspectives, using a balanced sample to mitigate gaps in previous studies by analyzing data in terms of diverse demography rather than from selected regions. However, since some studies consider results from a single location, future research can compare the complementarity, consistency, and coverage of single versus multiple locations, which will directly enrich the understanding of the findings presented here.

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