Operations Management Research (2024) 17:1213–1243
https://doi.org/10.1007/s12063-024-00492-2

The role of artificial intelligence in the supply chain finance innovation process

Alessio Ronchini[1] · Michela Guida[1] · Antonella Moretto[1] · Federico Caniato[1]

Received: 15 May 2023 / Revised: 11 April 2024 / Accepted: 23 April 2024 / Published online: 20 June 2024

Abstract
Leveraging on ten case studies, the paper examines the Supply Chain Finance (SCF) innovation process through a multiple stakeholder perspective (buyers, suppliers, and SCF providers). The aim is to identify the phases of the process impacted by Artificial Intelligence (AI), as well as its benefits and challenges. AI affects several activities in the Initiation phase of the innovation process, supporting the SCF provider's commercial activities and contributing to assessing the buyer's creditworthiness, detecting fraud, or proposing the right SCF solution. In the Implementation phase, AI supports assessing the supplier's credit rating, categorizing and onboarding suppliers, and fastening the administrative tasks. Formulating 9 propositions, this study supports the theory related to the SCF by providing empirical evidence about the role of AI in the SCF innovation process and also identifying the resulting benefits and challenges for all the actors involved.

Keywords Supply chain finance · Artificial intelligence · Innovation process

1 Introduction

There is a continuing interest in SCF among practitioners and the academic community. SCF refers to the optimization of the financial flows in the supply chain and its working capital, which involves external players such as financial and logistics service providers (Liebl et al. 2016). Gelsomino et al. (2016, p. 1–2) define SCF as "*a mix of models, solutions, and services aiming to both optimize the financial performance and control working capital within a supply chain, exploiting a deep knowledge of supply chain relations and dynamics*".

Today, global supply chains are even more exposed to uncertain and unpredictable events that jeopardize the continuity of business activities and commercial relationships (Moretto and Caniato 2021). As supply chains become increasingly complex, their exposure to these risk areas also increases. To address this uncertainty, organizations are beginning to employ advanced information systems to support their supply chains, thereby enhancing their capabilities such as transparency, better predictions, and faster decision-making (Saberi et al. 2019; Giannakis and Louis 2011; Gunasekaran and Ngai 2004). Advanced information systems encompass technologies like artificial intelligence (AI), which unleashes a significant portion of its potential in the critical decisions and activities in the supply chain, including SCF processes. Financial and technology providers are increasingly adopting AI to increase the service level and customize their offers (Zaks and Lapouchnian 2018; Song et al. 2021). AI can help companies better forecast their cash flows and decide the solutions to adopt and the suppliers to involve (Olan et al. 2022). However, the applications of AI have been poorly discussed in the SCF-related literature so far, lacking an understanding of the potential impacts it may have on SCF processes, the benefits its adoption could offer, as well as the potential challenges it may present. Aiming to fill this major gap, our research addresses the following research questions:

> **RQ1**: *How can AI support the SCF innovation process?*
> **RQ2:** *What are the benefits for buyers, suppliers, and SCF providers stemming from implementing AI in the SCF innovation process?*

✉ Alessio Ronchini
alessio.ronchini@polimi.it

[1] School of Management, Politecnico di Milano, Via Raffaele Lambruschini 4/B, 20156 Milan, Italy

RQ3: *What are the challenges for buyers, suppliers, and SCF providers stemming from implementing AI in the SCF innovation process?*

So, following the research direction identified by Guida et al. (2023), this paper leverages the innovation process developed by Rogers (2003) to understand how companies introduce the innovation brought by SCF solutions, together with the benefits and challenges faced by the different actors involved.

Lamoureux and Evans (2011) highlighted how the buyer firm, its suppliers, financial institutions, and technology providers are jointly involved in adopting SCF solutions. Therefore, in assessing the benefits and challenges stemming from the support of AI in the SCF programs, it is imperative to consider all the stakeholders impacted. Aiming to contribute in this research stream, our focus is the investigation of the primary actors involved in SCF solutions, as done by Moretto et al. (2019), that is the buyer firm, its suppliers, and, in this case, the SCF providers that offer the platform through which the buyer firm manages the SCF solutions. In fact, due to the digital transition that emerged in recent years, SCF is offered through digital platforms into which many financial institutions are integrated to offer their services.

Due to the exploratory nature of the topic, this research adopts the case study methodology, analyzing a sample of 10 SCF providers, as they represent the actors that develop SCF solutions supported by AI. Moreover, SCF providers are the only actors with a complete view of the SCF innovation process and solution implementation, as they can implement SCF solutions in different firms.

Our study of the support of AI in the SCF innovation process contributes to the reviewed literature in several ways. Firstly, the potential of AI in the SCF process is unveiled, describing how the technology streamlines the activities, identifies potential risks, detects fraud, optimizes working capital management, and reduces costs in SCF. Secondly, AI integration in supply chain management is not only a technical process but also a social one influenced by human sensemaking and managerial barriers. Understanding the role of AI in decision-making and its integration across the SCF actors is crucial for managing the adoption of AI in SCF. Lastly, this paper can inform cross-disciplinary collaboration and the development of sociotechnical perspectives, enhancing the theorizing and practice of SCF.

The paper is organized as follows: Section 2 presents the theoretical background of the paper; Section 3 explains the research framework and questions; Section 4 presents the research methodology; Section 5 displays the results from the case studies; and Section 6 discusses the findings. Finally, Section 6 concludes the paper.

2 Literature review

2.1 The SCF actors

A buyer firm activates SCF solutions to offer its suppliers better and privileged access to credit. Thus, the buyer firm signs a contract with a financial institution that provides liquidity to suppliers with different schemes according to the specific SCF solution (e.g., reverse factoring, confirmation, dynamic discounting). Many authors recognize the need to gain new knowledge about SCF, adopt a broader view, and consider all available solutions and the actors involved (Caniato et al. 2019). Bals (2019) proposed a new ecosystem-oriented perspective of SCF, wherein five stakeholders – buyer, supplier, solution provider, financial institution, and government – participate and have different roles during the SCF program. Wang et al. (2021) further developed a network-oriented perspective in which supply chain actors and financial providers partner for SCF solutions, creating the network capabilities that raise corporate financial performance. Lamoureux and Evans (2011) emphasized the collaborative involvement of the buyer firm, suppliers, financial institutions, and technology providers in implementing SCF solutions.

In line with the objective of the present research, we investigate the primary actors involved in adopting SCF, such as the buyer firm, the suppliers, and the provider delivering the SCF solution. Indeed, we take technology providers as key respondents as they offer SCF solutions through the digital platforms they developed on behalf of the financial institutions. AI is applied to the platforms to increase the service level offered to the buyer firm and its suppliers. Thus, we aim at satisfying one of the future research needs set by Bals (2019), i.e., investigating the opportunities generated by applying new digital technologies to SCF since they may improve processes and provide efficiencies, simultaneously hindering the SCF adoption (Song et al. 2021; Olan et al. 2022).

2.2 The SCF innovation process

Previous literature describes the alignment between physical and financial flows using several models. However, less attention has been paid to the steps required to reach this goal. In this direction and moving from the innovation adoption framework proposed by Rogers (2003), Wuttke et al. (2013b) first attempted to shed light on the steps of the SCF innovation process, which is intended as the sequence of several decision-making steps leading to the adoption of an SCF program. In particular, the SCF innovation process defines two phases, *initiation* and *implementation*, which are then subdivided into multiple subphases and activities (see Fig. 1).

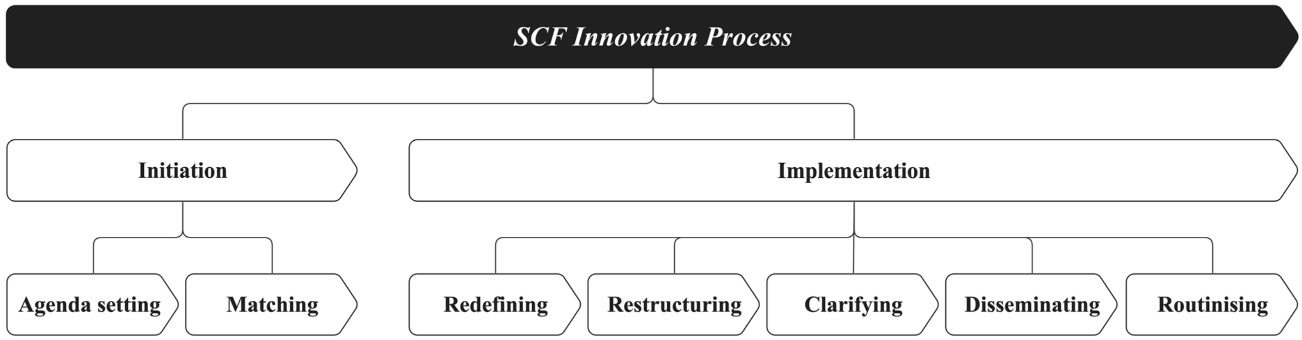

Fig. 1 SCF innovation process: adapted from Wuttke et al. (2013b)

The *initiation phase* starts with the needs of the buyer firm that can be satisfied through the adoption of SCF. This phase comprises two sub-phases: *Agenda Setting* and *Matching* (Rogers 2003). Thus, the buyer firm is firstly engaged in defining the problem it has from a financial viewpoint at a supply chain level, perceiving the need for a solution to adopt (*Agenda Setting*). Then, it spends time gathering information, conceptualizing, and planning for the adoption of an SCF innovation, identifying one or more possible SCF solutions, and leading to a decision (*Matching*). The initiation stage pertains to matching solutions offered by the IT provider and the transactional and relational characteristics in the buyer–supplier dyad. This topic is already investigated in the literature (de Goeij et al. 2021; Guida et al. 2021), but the impact of AI is still neglected. In commercial retail relationships, these AI solutions to identify consumer needs and the company's best response are more commonly discussed (Verma et al. 2021; Trawnih et al. 2022).

The *implementation phase* refers to the events, actions, and decisions in implementing innovation. As described by Rogers (2003) and echoed by Wuttke et al. (2013b), this phase comprises sub-phases: *Redefining*, *Restructuring*, *Clarifying*, *Disseminating*, and *Routinising*. In the *Redefining* sub-phase, the firm adjusts the SCF innovation to its specific context, designing the SCF solution for its own needs and reconsiders the contextual factors to which the SCF innovation needs to fit. Following a process-oriented perspective, the *Restructuring* sub-phase is needed to modify the organization's structure to fit with the innovation so that cross-functional collaboration, job redesign, and alignment of performance measurement systems can be achieved. Then, there is the need to onboard suppliers, and here the *Clarifying* and *Disseminating* sub-phases come. Firstly, upstream supply chain managers are persuaded about the importance and use of SCF to engage suppliers (*Clarifying*). Then, In the *Disseminating* sub-phase, the innovation diffusion is accelerated among suppliers that ultimately use SCF. As described by McKinsey&Co. (2015), one of the main success factors of the SCF programs lies in the "operational capability to ramp up programs and ensure they are profitable". The supplier perceives this as a core issue, as they are the ones to decide whether to onboard an SCF solution based on how quickly and easily that solution is put in place. Finally, in the Routinising sub-phase, the innovation is incorporated into the organization's routine activities, and continuous process improvement is sought. At the beginning of the implementation stage, several analytical activities are explicitly conducted for the SCF solutions, such as the analyses related to the creditworthiness of the actors involved (Zhu et al. 2019; Song et al. 2021). In addition, in the Implementation stage, the activities are related to the redesign of the tasks and organization of the procurement department, along with the other functions involved in the process, to sustain the change introduced by SCF solutions. This issue has never been studied considering the support offered by AI, as it was investigated from the organizational standpoint only (Wuttke et al. 2013b). In the implementation phase, the final activities are related to the routine of repetitive tasks. In routine activities, AI solutions are generically applied to the procurement process to enable data transfer between different information systems (Karttunen et al. 2023), or to make activities more efficient in terms of time and transactional cost with the supplier (Flechsig et al. 2022). From the SCF perspective, this issue has not yet been specifically addressed, and our research intends to bridge this gap.

The SCF innovation process has not been thoroughly investigated empirically, leaving Wuttke et al. (2013a) considerations without a natural evolution in subsequent research. This model highlights two intrinsically linked SCF adoption dimensions: the organizational (Bals 2019) and the decision-making dimensions (Guida et al. 2021).

Wuttke et al. (2013a) highlight how the financial benefits of SCF have always received more attention in the literature than the organizational aspects. Indeed, the financial benefits stemming from SCF justify its spread despite its adoption being complex and organisationally challenging (Seifert 2010). Among the organizational hurdles, More and Basu (2013) identified the lack of SCF knowledge transfer between buyers and suppliers and the missing training measures in the adoption; Wandfluh et al. (2016) identified issues related to the organization's structure in the set-up of SCF programs.

Bridging the line between the organizational and decision-making dimensions leads to the ownership of SCF within companies (Bals 2019). Several authors highlighted the primary decision triggers in analyzing the adoption of SCF solutions. Caniato et al. (2016) investigated the objectives of the focal firm in initiating SCF. They identified four moderating variables in the decision-making process: the level of trade process digitalization, the bargaining power between the involved parties, the financial attraction towards the service provider, and the relevance of collaboration in the SCF solution implementation. Coherently with this approach, other contributions addressed the characteristics of the buyer–supplier relationship in terms of mutual trust, cumulative transaction value, information sharing, and strategic interdependence since they have an overriding influence on the decision process of SCF (de Boer et al. 2015; Guida et al. 2021; Zhang et al. 2021). The study by Banerjee et al. (2021) takes the supplier's perspective in adopting digital reverse factoring solutions. It reveals the importance of behavioral elements, trade-offs between financial and non-financial benefits perceived by the supplier, and expectations in the technology in terms of transparency and visibility.

Although some elements support the managerial decisions presented, guidance for SCF adoption should encompass a deep understanding of the innovation process engaged by the firm in terms of activities and decision-making gates. Current knowledge needs to investigate the activities involved in the SCF innovation process, the role of technology tools, and the benefits and barriers arising from SCF innovation.

2.3 AI in SCF

In the last twenty years, literature has started looking into the relevance of AI for purchasing and supply management (PSM). This is even more true in recent publications (e.g. Toorajipour et al. 2021; Guida et al. 2023). In the PSM domain, AI is most perceived as the support provided to managers in solving practical problems: "*Artificial Intelligence is referred to as the use of computers for reasoning, recognizing patterns, learning or understanding certain behaviors from experience, acquiring and retaining knowledge, and developing various forms of inference to solve problems in decision-making situations where optimal or exact solutions are either too expensive or difficult to produce*" (Min 2010; pp. 13–14). The most relevant techniques to this paper are listed in Table 1. They have been taken by Guida et al. (2023), who compile the main functionalities of AI in the purchasing and supply domain.

Scholars investigated AI's contribution to inventory control and stock optimization, directly connected with cash-to-cash cycle optimization and SCF. Priore et al. (2019) showed how machine learning (ML) allows the dynamic selection of the best replenishment policy within a fast-changing supply chain environment. Badakhshan et al. (2020) studied how to reduce the cash flow bullwhip effect, i.e., the inefficiency in cash distribution along the supply chain, through a simulation-based optimization approach that integrates system dynamics simulation and genetic algorithms.

AI is developing and re-shaping SCF solutions and ecosystems in the SCF domain, directly impacting stemming performance (Chen et al. 2021). The most widespread adoption of AI is related to the credit risk assessment process (Khashman 2011; Zhu et al. 2016, 2017, 2019). To forecast credit risk, traditional statistical approaches are characterized by a main drawback, i.e., they assume a specific data distribution that requires substantial historical data (Zhu et al. 2019). On the contrary, ML approaches (a typical form of AI) do not need to assume a priori data distributions.

Table 1 AI techniques

Natural Language Processing (NLP)	"Natural Language Processing is a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis to achieve human-like language processing for a range of tasks or applications" (Liddy 2001)
Recommendation system	"Recommender systems can be defined as programs which attempt to recommend the most suitable items (products or services) to particular users (individuals or businesses) by predicting a user's interest in an item based on related information about the items, the users and the interactions between items and users" (Lu et al. 2015 – p. 12)
Robotic Process Automation (RPA)	Robotic Process Automation (RPA) is defined as "a preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management" (IEEE Corporate Advisory Group 2017)
Virtual Assistant or Chatbot	"A chatbot system is a software program that interacts with users using natural language" (Shawar and Atwell 2007 – p. 29)

They may achieve acceptable forecasting accuracy, even when the dataset is small. Furthermore, it has been demonstrated that the performance of ML is generally better than that of traditional statistical approaches, especially for classifying limited data with a nonlinear distribution (Khashman 2011; Zhu et al. 2019). Mentioning recent research, Song et al. (2021) conceive AI techniques as a support for financial service providers in assessing the supply chain credit of small and medium enterprises (SMEs) and discriminating the quality of SMEs to be supported through appropriate SCF solutions.

In assessing risk, an increasingly common approach is the inclusion of unstructured data sources and advanced analytics to allow credit evaluation in SCF programs (Fu and Zhu 2016). This phenomenon is predominantly observed in Fintech companies (Li 2018) that have yet to establish long-established relationships with the buyer firms to which they offer SCF solutions and need to find ways to learn more about their creditworthiness through available data (Hung et al. 2020) This is especially true when well-structured financial statements are absent, such as for SMEs. Therefore, Fintechs deploy powerful data collection and analysis tools to address fraud detection issues and prevent any possible risk related to working capital financing (Chen 2015; Hung et al. 2020).

In addition, as the players involved in an SCF solution become increasingly connected, SCF data has grown massively, and the potential for supply chain financial fraud has exploded: AI can significantly support the prompt detection of fraud patterns (Zhou et al. 2020).

Despite these preliminary attempts, there is still a gap in the academic literature regarding the use of AI in the SCF domain, along with the resulting benefits and challenges. This gap is specially oriented to understanding how AI might support the SCF innovation process, considering the perspective of all the actors involved.

2.3.1 Benefits of AI

As the role of AI in SCF still needs to be investigated in literature, it is difficult to identify the benefits achieved through the technology. For this reason, AI gains in SCF are mainly described as expected benefits in broader terms, drawing on the literature recounting AI in the PSM domain and selecting valuable insights for the narrower SCF domain.

Looking at the efficiency dimension, the main benefits of AI concern the reduction of cost of funding (*cost saving*) and the decrease of the duration of administrative procedures (*faster processes*). Indeed, the cost dimension of SCF solutions is a widely debated issue in the literature (Wuttke et al. 2013a) and well-represented even when SCF is supported by AI (Bousqaoui et al. 2017; Zhu et al. 2019). Looking at the time spent in administrative activities for the SCF, Gottge et al. (2020) describe the improvements in decision-making from AI in procurement, which reduces uncertainty and facilitates faster process times as the main benefits.

AI enhances SCF in terms of effectiveness as well. Brintrup et al. (2024) leverage AI techniques to predict possible discontinuity events along the supply chain. This application significantly benefits supply risk management (*risk reduction*), even when it concerns credit risk (Zhu et al. 2019; Song et al. 2021) and cash flow forecasting (Badakhshan et al. 2020). Recently, the support of AI for fraud detection has gained attention, both in procurement and, more specifically, in SCF. Zhou et al. (2020) describe big data mining as detecting suspicious actions among the actors in a supply chain.

Kamble and Gunasekaran (2020) claim the importance of unlocking the benefits of intelligent systems in supporting planning and sourcing decisions: they bring reliable advice in planning for supply chain decisions and cash forecasting (*enhanced services*).

2.3.2 Challenges of AI

The challenges in adopting AI in PSM, specifically in SCF, are still numerous and heavy. Among them, *data availability and management* still need to be improved in many companies, preventing the proper adoption of AI (Chehbi-Gamoura et al. 2020; Amankwah-Amoah and Lu 2022). Hazen et al. (2014) tackle the data quality issue affecting supply chain management. Kache and Seuring (2017) describe data availability from a different perspective, looking at the issue of cyber security at the company and supply chain level, which is a relevant issue in the SCF domain.

The *collaboration* between the actors involved also plays a crucial role in trust and information sharing. Recognizing that supply chain networks are made of dispersed nodes, Shore and Venkatachalam (2003) developed an algorithm to evaluate the supplier information-sharing capability based on two fundamental characteristics: the collaboration level and the information technology infrastructure.

Change management is affecting the adoption of AI in PSM applications. It can be described as an awareness of AI and organizational procedures and processes (Bienhaus and Haddud 2018). Indeed, processes are affected by digital transformation, and employees can be part of the successful adoption of AI by identifying areas for improvement.

Another challenge to overcome is the top-management prioritization of *investment cost and budget* (Handfield et al. 2019; Bienhaus and Haddud 2018). Indeed, investments in new technologies are often dedicated to other business functions that are considered more profitable.

3 Research objectives and research framework

Extant contributions investigate the impact of AI in supporting supply chain processes other than SCF: material replenishment (Priore et al. 2019), demand forecasting (Bousqaoui et al. 2017), and supplier selection (Wu et al. 2009) are some examples. In dealing precisely with SCF, all the contributions pertain to risk management and creditworthiness assessment (e.g., Badakhshan et al. 2020; Hung et al. 2020). However, in academic knowledge, there must be more at the intersection between AI and SCF. Confirming this, Guida et al. (2023) advise that future research should focus on the SCF adoption process to study the role of AI. Adopting AI in the SCF innovation process brings a twofold component of novelty: the adoption of SCF solutions and the additional innovation of AI. For this reason, Rogers' innovation process is taken as the reference theoretical structure, building on the suggestions in the paper by Guida et al. (2023).

The only contribution addressing a portion of the SCF innovation process is the application of machine learning techniques supporting credit risk evaluation (Zhu et al. 2016, 2017, 2019; Khashman 2011). However, credit risk assessment is just one of the stages within the SCF innovation process.

Addressing these gaps, this paper first analyses the support of AI in all the phases of the SCF innovation process, namely the *initiation* and *implementation* phases and related sub-phases (see Fig. 1). Research Question 1 (RQ1) summarises this objective:

RQ1: *How can AI support the SCF innovation process?*

SCF solutions involve multiple actors (Gelsomino et al. 2016), mainly three essential players: two actors that adopt the SCF solution (i.e., the buyer and the supplier) and one actor that provides support for the implementation of the SCF solution (i.e., SCF provider). Dealing with adopting AI in the SCF innovation process, each actor has a clear role, gaining the related benefits and facing the challenges that arise. Although previous contributions have investigated the challenges and benefits of SCF (e.g., Nguyen et al. 2018), the specific benefits and challenges arising from adopting AI throughout the SCF innovation process have never been addressed. Therefore, the second objective of this paper is to investigate the benefits and challenges impacting the buyer firm, its suppliers, and the SCF provider, addressing Research Question 2 (RQ2) and Research Question 3 (RQ3):

RQ2: *What are the benefits for buyers, suppliers, and SCF providers stemming from implementing AI in the SCF innovation process?*
RQ3: *What are the challenges for buyers, suppliers, and SCF providers stemming from implementing AI in the SCF innovation process?*

Figure 2 shows the Research Framework used to answer RQs.

4 Research methodology

The case study methodology was selected in line with the explorative nature of this research (Eisenhardt 1989) and its theory-building characterization (Voss et al. 2002). Multiple case studies were chosen to collect rich qualitative insights to conduct a robust analysis from multiple perspectives.

4.1 Sample description

Since the research focuses on the impact of AI on the SCF innovation process, empirical data were collected through 10 case studies involving SCF providers, as they represent the primary informants that enable AI-supported SCF solutions. These 10 firms agreed to be interviewed and studied. However, they were part of a total sample of 64 providers that were identified through research on LinkedIn and on search engines on the internet using keywords such as *Supply Chain Finance technology providers/companies, Artificial Intelligence providers/companies, Supply Chain Finance providers using Artificial Intelligence, financial technology providers, technology providers of financial services, Supply Chain Finance solutions providers, technology providers in Supply Chain Finance, Artificial Intelligence providers/companies in Supply Chain Finance.* The unit of analysis is the solution offered by the provider and how this solution is changed through the use of AI—the involvement of solutions providers as key respondents is supported by previous research in the same context. Handfield et al. (2019) and Yarramalli et al. (2020) take the same perspective in the PSM domain. In SCF, Ronchini et al. (2021) developed multiple case studies involving 15 SCF providers. Our choice to involve SCF providers stems

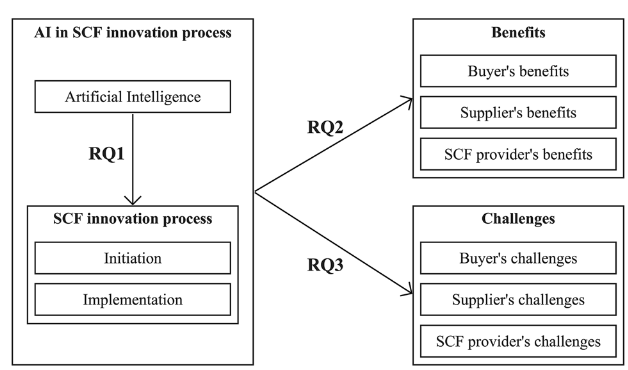

Fig. 2 Research framework

from several reasons. First, they implement SCF solutions with different buyers and suppliers, bearing the knowledge about many cases they have implemented, rather than interviewing a buyer firm only reporting its specific case (Ronchini et al. 2021). Second, SCF providers are the initiators of the SCF innovation process, often advising the buyer firm and its suppliers in adopting SCF solutions so they know the activities and the critical issues in the SCF innovation process (Jia et al. 2020b). Third, they are the most informed actors about the application of AI in the SCF process, as they develop and provide AI-based SCF solutions for user firms (i.e., the buyer firm and the suppliers). Thus, thanks to their ownership of the SCF innovation process, they know the technological structure underlying the solution and the benefits and challenges. It is especially true regarding AI, as the user companies lack adequate knowledge of AI. The buyer firm and the suppliers perceive AI as a general-purpose technology, i.e., a generic technology that is single and recognizable, whose potential grows as its applications, the related infrastructures, systems, and skills increase (Crafts 2021).

The sample was designed to achieve purposive sampling (Schreier 2018) to ensure the companies involved currently provide AI-based SCF solutions or related services, bringing a distinct view of the research question. It includes firms from different countries with a worldwide-spread client base and a heterogeneous role within the SCF ecosystem by offering different SCF solutions supported by AI (see Table 2). The sample encompasses both providers that offer SCF solutions through their platforms (i.e., companies A, B, C, E, F, G, J) and providers that offer SCF supporting services such as supply chain process digitization, credit rating assessment, and consulting (i.e., companies D, H, I).

Companies part of the sample are representative companies in the SCF domain, with a strong reputation in the industry and the offering of SCF solutions for several years when this is not the only domain of the company. To have a comprehensive view, Annex A reports the list of the leading SCF solutions from Guida et al. (2021), describing them and the different actors' role in the solution scheme. Moreover, the companies consistently introduce AI, not just as a claim. For these reasons, the sample could be considered a good representation of the industry under investigation.

4.2 Data collection

The data were collected through information retrieved from secondary sources and direct interviews with firms' representatives to triangulate the information.

Starting from secondary sources, we first tried to collect data and information about the AI-based SCF solutions the players in the sample provided. The first sources were their websites, where providers showed their offers regarding SCF and related solutions. When white papers and case studies (in the form of a report) were available on their site, we downloaded and used them to complete the information needed to study the case. In addition, we had already conducted research with companies A, C, E, G, H, and J and had additional valuable data available for the study. This information was essential to extrapolate additional data to validate what SCF providers stated during the interviews and add information about the context and the solutions offered, consistent with the insights of Eisenhardt (1989) and Yin (2018).

These insights supported the development of the semi-structured interview protocol (see Table 3), adopted in the

Table 2 Case study sample

Case Studies	SCF solution(s)	HQ Location	Foundation Year	Size of the company (Revenues)	Role of the Interviewees	Number of interviews
Company A	Dynamic Discounting	USA	2008	6,39 M$	Managing Director	2
Company B	Working capital financing, Virtual credit card	USA	2006	725 M$	Sales Director	1
Company C	Reverse Factoring	ITA	2015	15,4 M$	Product Manager/Data Scientist	2
Company D	Business process digitization	FRA	2018	< 1 M$	Founder and CEO	1
Company E	Factoring, Reverse Factoring	UK	1972	25,5 M$	Regional Commercial Director	1
Company F	Factoring	EST	2013	< 1 M$	Founder and CEO	1
Company G	Reverse Factoring, Dynamic Discounting	USA	2000	72 M$	Product Director Working Capital Solutions	2
Company H	Credit rating	ITA	2006	7,9 M$	Co-founder and CEO	2
Company I	Working capital management and financing	CAN	2018	1,5 M$	President and CEO	1
Company J	Factoring, Reverse Factoring, Virtual credit card	USA	2009	57 M$	Account Executive	2

Table 3 Case study protocol

Supply Chain Finance services general information
What Supply Chain Finance solutions does your company offer (e.g. Reverse Factoring, Inventory Financing, Dynamic Discounting, etc.*)*
How many customers does your company serve with SCF solutions?
How does your platform establish a connection between companies and financial institutions?
What are the most common needs that your customers want to satisfy by adopting your solutions?
Supply Chain Finance Process
At the first contact with your customers, are they already oriented to a SCF solution to solve their needs or do they require to be informed about the potentialities of SCF?
When they require to be informed, how do you support your customers in selecting the solutions more suitable to satisfy their needs?
How do you support your customers in doing a screening of their supply base to evaluate which suppliers are eligible to a SCF program?
How do you support your customers for the onboarding of suppliers, in order to convince them to accept the SCF innovation?
How do you support your customers in spreading awareness and training their own employees about SCF?
How do you support your customers in disseminating the SCF innovation among their suppliers and in training the selected ones about the use of SCF solutions?
Which functionalities does your platform provides during the execution of the implemented SCF solutions?
Artificial Intelligence in the Supply Chain Finance Process
Do you adopt Artificial Intelligence to serve your customers?
In which of the SCF innovation process phases do you use the Artificial Intelligence?
Which is the value added by Artificial Intelligence to each specific phase?
How does the AI algorithm work? (inputs required and outputs provided)
Supply Chain Finance & Artificial intelligence: Benefits and Challenges
What are the benefits for a technology provider of using the AI to support the SCF process?
What are the challenges for a technology provider of using the AI to support the SCF process?
What are the benefits for a buyer to rely on a SCF platform which is supported by Artificial Intelligence?
What are the challenges for a buyer to rely on a SCF platform which is supported by Artificial Intelligence?
What are the benefits for the suppliers engaged in a SCF solution which is supported by Artificial Intelligence?
What are the challenges for the suppliers engaged in a SCF solution which is supported by Artificial Intelligence?

primary data collection. Direct interviews with decision-makers were performed with each firm to complement data collected through secondary sources and especially exploit the perspective brought by different actors. Respondents to the interview were selected, identifying the person responsible for the SCF solutions and who was part of the process of introducing AI in the company. We first approached pure technology providers offering one or more SCF solutions. When we recognized that respondents provided similar answers to the same questions, we moved on to tech providers offering other services, such as business process digitization and credit rating. We acknowledged that we had achieved a high saturation level as we were not collecting any innovative insight by the new technology providers, so we ended up the data collection process. Questions were anticipated before the interviews to increase the validity of data collection in a twofold way: the possibility of identifying the right person to be involved in the interview and the possibility of collecting pieces of information from other internal informants.

Interviews lasted approximately 60 to 90 min each. We conducted two interviews with companies A, C, G, H, and J, while the others granted us only one interview. Despite this, we collected the necessary data to conduct the study as we arrived at the interview with a complete set of information at hand retrieved through secondary sources. Thus, in the time available, we focused mainly on the core topic of the research and on validating those pieces of information. The interview protocol was used as a checklist, more than a guideline, leaving room for spontaneous insights raised by the interviewees. Interviews were recorded and transcribed, being the input for the data analysis. In addition, we completed the data through e-mail exchanges with the interviewees without little details.

4.3 Data analysis

Content analysis was performed through a coding process. A detailed coding tree (see Annex B) was leveraged to encode the raw data, in line with the suggestions by Eisenhardt and Bourgeois (1988). In designing the coding structure, codes were identified while defining the research framework based on the literature review. However, when innovative insights emerged from the interviews, new "in vivo" codes were added to encode the findings from the interviews properly. To ensure the rigor of the process and the validity of the new codes, the data analyses have been performed separately by two researchers. As expressed in the research by O'Connor and Joffe (2020), a minimum of two coders is essential to guarantee the reliability and rigor of the coding process. Moreover, as O'Connor and Joffe (2020, p. 6) emphasized, *"the two coders should act independently without conferral"*. The results of the two coding processes have been compared among the two researchers, who worked together to develop a unique version of the results, in line with the practice explained by Syed and Nelson (2015). Doubts that emerged from the data analyses (e.g., differences and difficulties in coding pieces of information from interviews, misalignments in new codes) were resolved through a meeting in which all the authors participated and contributed to the definition of a unique understanding and coding of all information and data. It has enhanced the internal validity of the research (Syed and Nelson 2015; O'Connor and Joffe 2020).

With a clear structure of the data, the analyses started. First, a within-case analysis was performed to understand the constructs' relationships within each case. Then, the cross-case analysis allowed us to highlight convergence or divergence among the 10 cases, answering to RQs (see Annex C). The final research framework was created at the end of the data analysis. The findings from the case studies are derived through inductive reasoning (Mantere and Ketokivi 2013), combining the observation of the actual phenomenon (i.e., the implementation of AI in the SCF innovation process), with the explanations coming from previous knowledge (see the coding tree in Annex B).

To assess the rigor and validity of the research process and results, Table 4, based on Gibbert et al.'s model (2008), provides information regarding internal, external, and construct validity and reliability.

5 Results

The empirical evidence gained from the case studies informed us in crafting the final research framework (see Fig. 3), where all the relevant constructs (i.e., the SCF innovation process, the benefits, the challenges) are interpreted in the phenomena investigated (i.e., the role of AI in the SCF innovation process.

5.1 AI in the SCF innovation process

From case studies, we identified the phases and sub-phases of the SCF innovation process supported by AI (see Fig. 3). AI plays a role in the *Agenda Setting* and *Matching* sub-phases in the initiation phase. The implementation phase is impacted in the *Redefining, Disseminating,* and *Routinising*

Table 4 Validity and rigor of the research process—model by Gibbert et al. (2008)

Variable	Description of the validity/reliability	Source of validity/reliability
Internal validity	The constructs and the research framework have been deducted from the literature review. Codes result from identifying the relevant variables in the academic literature at the intersection of SCM, SCF, and AI in SCM and SCF. Results have been compared with the results of the literature review	Refer to the theoretical background, coding tree, methodology, and discussion of the results
External validity	Information and data have been collected from different providers of SCF solutions and related services that integrate into the Artificial Intelligence. Results have then been presented to informants and other experts on AI and SCF to validate them and ensure that information has been well interpreted	Refer to the case study sample (Table 2) and the cross-case tables (Annex C)
Construct validity	Data and information have been collected predominantly from primary data from experts on the research topic. Data have been further triangulated with secondary sources to enhance data collection. 2 researchers performed data analyses, and results were compared and validated among authors in a dedicated meeting. Data analyses have been explained, and cross-case tables have been provided	Refer to the case study sample (Table 2), the interview protocol (Table 3), and the cross-case tables (Annex C)
Reliability	The coding tree has been provided, and all the variables have been explained in the theoretical background section. The interview protocol and the cross-case tables have been explained and provided	Refer to the coding tree (Annex B), the interview protocol (Table 3), and the cross-case tables (Annex C)

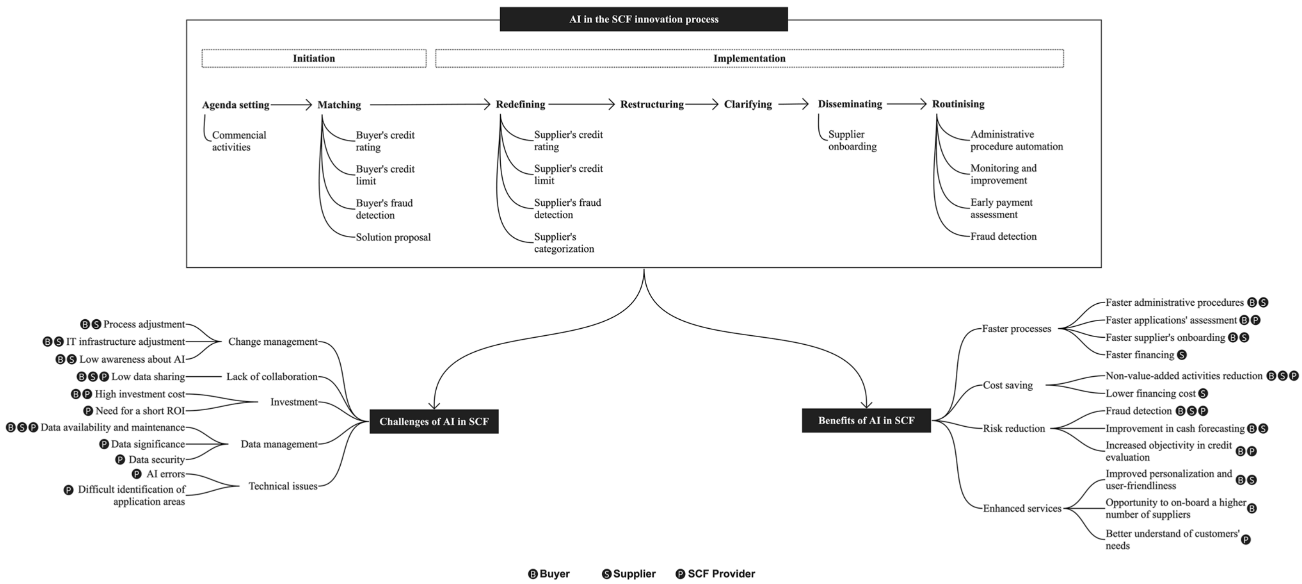

Fig. 3 The support of AI to the SCF innovation process – a framework

sub-phases. There is no evidence of using AI to support activities during the *implementation phase's Restructuring* and *Clarifying* sub-phases. Indeed, organizational activities such as internal alignment and engagement for SCF implementation are conducted during these stages without technological support, making them relational activities. In the SCF implementation phase, AI generally helps make informed decisions, streamline the process, and automate and support the day-to-day operational activities.

In this section, we describe the role of AI in each of the phases of the SCF innovation process, referring to the results from the case studies (detailed quotations are provided in Table 5).

5.1.1 Initiation

In the ***Agenda Setting*** sub-phase, *AI supports commercial activities* that SCF providers primarily use to forecast cash flows for their clients. Company I stated that AI makes it possible to understand a firm's cash flow accurately to detect which customers need a SCF solution and, consequently, perform some commercial activities towards the identified targets. Related to this, Company C stated that they use AI by leveraging clustering techniques to classify companies and to target the most promising ones. Through predictive analytics, Company E can understand if its clients will have cash flow problems and, consequently, offer new financing services by up-selling or cross-selling. It is evident that during this stage, the player benefiting most from AI is the SCF provider, which uses data to analyze its clients to offer them new services. It is also aligned with the research's first attempts to focus on the initial activities of the SCF innovation process, as Song et al. (2021) investigate how to customize the SCF offer based on the firms' needs involved in the program. Despite of this, it is worth saying that AI uses historical data to make solutions' proposals. It is an evaluation related to a pre-defined pattern that the algorithm is familiar with, instead of proposing an innovative solution that moves away from pre-established patterns drawn from SCF's cash flow and usage history. Thus, the technology is fundamental in forecasting potential uses of SCF, but the human intervention is fundamental in advancing customized and innovative solutions proposed in accordance with the deep knowledge of the need of the company (De Bruyn, et al. 2020).

After *Agenda Setting*, the ***Matching*** sub-phase is initiated. Here, the buyer realizes that an SCF solution is required to satisfy its needs, and consequently, this phase aims to identify the most proper SCF solution.

The first activity supported by AI is the *proposal for solutions*. Company G describes its support to clients in the decision to implement an SCF solution by providing advanced information about the supply chain's financial flow, which shows the returns on the investment for each SCF solution available. Standard technologies cannot perform such analyses by combining all the currently available data: transactional data from ERPs, information providers, insights from credit rating agencies, and other industry benchmarking about liquidity and payment terms.

Then, the most impacted activities, highly enhanced by AI, are the *buyer's credit rating assessment* and the *buyer's credit limit* definition. Indeed, once a buyer adopts an SCF solution, the provider must evaluate the buyer's credit rating. Case studies highlighted the importance of this activity and the support of AI algorithms: thanks

Table 5 Quotes from case studies – SCF innovation process

Initiation
Agenda Setting
Commercial activities “We started working on AI’s potential contribution in the initial phase when the buyer’s cash need is assessed. It will be an important feature, especially from a general market perspective, clustering all the Italian companies and figuring out which ones to target with our marketing initiatives” – Company C
Commercial activities “Our mapping includes the analyses of data to provide predictive insights, so as the bank would know in advance if the clients would have cash flow problem in the coming month, approaching them with new financing products” – Company E
Matching
Solution proposal: “Based on the request made by the buyer firm, an investigation is formulated. First, the algorithm is run; then, there is the final evaluation and judgment by the analyst. The algorithms make a proposal about the SCF solution to be implemented” – Company C
Buyer’s fraud detection: “We have a data extraction tool. It connects the ERP of buyers and suppliers and automatically extracts transactions. We crunch this data with risk management algorithms according to different indicators tailored to industries. Several analyses are run: fraud and collusion, contractual conditions, risks assessment more in general.” – Company E
Buyer’s credit rating and **Buyer’s credit limit**: "We onboard the supplier, we run a background check on the supplier. The same applies to the buyer. Part of this information is automatically pulled from different registries, credit bureaus, public data of the government, published data. We combine this data with the financials and bank account statements of the firms involved. In this way, everything is visible for the credit specialist." – Company F
Buyer’s fraud detection: “Technology supports many features, starting from fraud risk, financial risk, credit risk, legal risk.” – Company F
Buyer’s credit limit: “We have some spend analyses that gather all the payables and receivables from our prospects and do some analyses to explain them how much cash flow they can unlock from their supply chain, how they can negotiate the payment terms with their suppliers according to some industry benchmark. So, we build business cases showing the buyer’s credit limit and the return on investment based on data from the company.” – Company G
Buyer’s fraud detection: “Our algorithm intervenes if there is a demand to assess every aspect of risk. We analyse the risk associated with a large buyer, and also the suppliers to see which ones are best suited for an SCF solution. AI solutions are useful for pre-selection activities, rating, monitoring, and intervention of internal information that can change ratings. There we intervene with custom or even ad hoc solutions.” – Company H
Implementation
Redefining
Supplier’s categorization: “We pull in the system the last information we have of suppliers, whether they are using our solutions or not. We integrate our information with external data sources, such as credit agencies. We pull data into our supplier assessment tool, to understand their need for our solutions. We do a quite sophisticated analysis, using more machine learning than AI, because in that area it works very well.” – Company A
Supplier’s fraud detection and **Supplier’s categorization**: “We analyse the performance and the risk associated with each supplier in advance, because we crunch data from public databases (e.g., Thomson Reuters). We analyse public judicial data, web sentiment relating to the news of a specific supplier, we cross-reference this information with any other sources the buyer firm may wish to add (e.g., Cerved, Ecovadis). Then we give a score to each supplier, which are classified as trusted, normal, and untrustworthy.” – Company B
Supplier’s credit rating and **Supplier’s categorization**: “We run a data analysis to understand which companies in the supply base may be interested in our solutions, together with the probability of usage of our solutions. A set of the algorithms we run is for commercial purposes. An example is the estimation of the optimal price to be offered to a company you want to bring on board.” – Company C
Supplier’s categorization: “Once the buyer firms buy the project, we can also help them in categorize the suppliers to target first, because they have higher value of invoices with longer payment terms.” – Company G
Supplier’s credit rating and **Supplier’s credit limit**: “We build highly customized intelligent decision-making engines designed to generate credit risks decisions in near real-time, also identifying the supplier credit rating and setting the limit. You can run several solutions to measure and mitigate various risks.” – Company I
Supplier’s categorization: “The inherent flexibility of our suite of self-learning AI tools allows fine-tuning our solutions based on the needs of a broad spectrum of corporate users, across the entire supply chain finance ecosystem, including buyers, financiers, and suppliers.” – Company I
Supplier’s categorization: "Our solutions can be used to cluster the suppliers to be onboarded and to select the best solutions for the suppliers we want to engage. In this way we can display many possibilities to the suppliers, also explaining the potential benefits." – Company J
Disseminating
Supplier onboarding: "AI can support the disseminating of the solution, by engaging the right supplier. We are trying to onboard the suppliers ourselves, finding the right people to talk to, have the right conversation, the right timing, providing the right information, and proposing the right SCF solution. The insights coming from AI are very supportive in that." – Company A
Supplier onboarding: “Now that we use this solution to advance the invoice payment, we want to educate others, such as our minor suppliers, who never even thought about thinking that way” – Supplier firm describing the AI-based SCF solution of Company A
Supplier onboarding: "We also have an online supplier onboarding tool based on AI. Our idea for the next future is to add analytic tool for tracking suppliers’ behavior and use AI to improve the automated workflow as the onboarding is one of the biggest challenges in SCF." – Company E

Table 5 (continued)

Initiation
Routinizing
Early payment assessment: "Our smart algorithms can optimize how the cash is allocated to the suppliers according to a priority based on their need" – Company A
Monitoring and improvement: "We have the spend guard, which allows the buyer to analyze all the transactions within the company, detecting and reporting maverick buying or other suspicious behavior thanks to AI." – Company B
Administrative procedure automation: "AI supports what we call mapping, referred to as document management and administrative procedures. These activities are time-consuming and are not adding real value, AI mapping is automatically able to understand the file format and make the mapping." – Company D
Administrative procedure automation: "AI mapping supports the so-called massive EDI: buyers want that all their suppliers send invoices automatically by EDI." – Company D
Monitoring and improvement: "We have a tool for reconciliation thanks to the integration with a third party. It has the capability to extract data from different bank accounts and provides specific algorithms to allocate these transactions through AI. AI allows improving allocation." – Company E
Monitoring and improvement: "We invest in R&D for AI, banks can control through the platform the creditworthiness of their debtors, who is paying on time, who is eligible for payment discounts, payment forecasts. We also integrate with data provided by the credit insurance companies." – Company E
Administrative procedure automation: "We are using artificial intelligence also in cash reconciliation, so we match payables and receivables with the actual payment that is a manual process today, and we are automating this process using artificial intelligence." – Company G
Early payment assessment: "We also use AI to understand the past behavior and anticipate the future one. If you know that the supplier over the last 3 years always request financing at the end of each quarter so maybe in the future, we can suggest activating this option automatically." – Company G
Fraud detection: "Fraud solutions use AI to check that invoices are not duplicated through the platform, or other wrong behavior." – Company G
Early payment assessment: "The price of dynamic discounting can be determined completely dynamically easily using some AI" – Company I
Administrative procedure automation and **Fraud detection**: "One of the main time-consuming activities is the invoice management, as the buyer waste time in deciding the reference accounting item for the invoices. Our solution is able to automatically identify the accounting item for each invoice based on the analysis of past data. The same applies to the data cleaning and the identification of recurrent mistakes or inefficiency in the administrative procedures."– Company J
Administrative procedure automation: "Provider J' s solution helps our administration in invoice management. We only need to upload the invoice to the portal, and this allows us to have traceability and reconciliation of all information automatically. We have visibility of the invoice; we can see if the invoice was fine if the buyer has approved it and then if they will pay it." – Supplier firm describing the AI-based SCF solution of Company J

to the technology, several types of data are combined to achieve the desired output rapidly, maintaining the objectivity and accuracy of assessments that are impossible with traditional analyses. Moreover, the buyer credit rating computation is often accompanied by the credit limit definition, i.e., the maximum financial exposure granted to the borrower. Providers show high confidence about the capabilities of the technology in better assessing the risks associated with the SCF solutions. Still, in previous literature there is scepticism. For instance, Biju et al. (2024) have recently highlighted the presence of potential bias in the algorithms leading to inaccurate risk assessments and predictions. Despite the overspread use of machine learning for credit risk evaluation, the actual quality of the outcome of the algorithm should be furtherly studied.

Fraud detection is a further relevant activity performed by SCF providers when new customers approach their services, and case studies show that AI can significantly increase the reliability of these analyses. Companies C and I stated that fraud analysis is not simply about transactional risks but also about the risk of encountering a fake company or even a network of fake companies. Thus, through AI, it is possible to detect superficial irregularities in balance sheets or bank accounts, also considering social media-related information, such as online presence, that, as Company C's Product Manager stated, *"make us feel safe"*.

The abovementioned results show that AI primarily supports the SCF provider in the *Matching* phase, especially in proposing the most proper solution to the buyer firm and assessing the risks related to the different financial transactions.

5.1.2 Implementation

The objective of the implementation phase is to set up the SCF solution selected. The buyer firm should decide which suppliers to involve, assess, and onboard. AI strongly impacts several activities in this phase.

Within the ***Redefining*** sub-phase, *supplier categorization* is critical to identify the most suitable suppliers to be involved in the solution, and AI can significantly impact this decision.

Company C uses AI to estimate the so-called "probability of usage" for each supplier in the buyer's supply base. Similarly, Company B analyses and classifies suppliers through AI by using the data from performance records, public databases, information from web sources, and social media. In the experience of Company C, suppliers must be approached with the right SCF offer as the SCF solution *price* is the primary driver in their decision. The SCF solution must be beneficial for the supplier and well communicated to avoid either the supplier accepting unattractive offers or rejecting attractive ones, as explained by de Goeij et al. 2021. In this direction, AI helps to properly manage the complexity of a multi-attribute decision-making process, given the large amount of information that should be analyzed to target the best suppliers with SCF appropriately.

For each supplier, *supplier's credit rating assessment* and *supplier's credit limit definition* are then performed. These analyses are the same performed in the *Matching* sub-phase for the buyer firm and are now focused on suppliers. Some providers involve other partners to perform these activities: Company G relies on an insurance company that applies AI-based rating methodologies specifically designed for SMEs. Moreover, by calculating the risks associated with each supplier, the insurance company also suggests which discount to apply for each SCF transaction. Company C also performs this analysis, which has already implemented AI to evaluate and support pricing decisions, which means that they try to estimate the optimal price to offer to suppliers considering their usage probability and their credit risk evaluation.

Another assessment that is performed is the *supplier's fraud detection,* similarly to what emerged in the matching sub-phase for the buyer firm. Company G states that when a new supplier is onboarded, they leverage on AI to scan the blacklist of the country of origin quickly and to perform the screening of transactions. Risk analyses on suppliers are compulsory for SCF programs in multiple countries, such as Italy, and AI helps conduct such assessments effectively.

In the ***Disseminating*** sub-phase, the objective is to convince the suppliers to participate and use the SCF program. The *supplier' onboarding* is generally very costly and time-consuming, but advanced tools based on AI can drastically streamline it. Company A can engage new suppliers by leveraging intelligent virtual assistants that can explain the proposed solution, simultaneously providing the correct and timely information to different actors. Company E adds information: "*We also have an online supplier onboarding tool with Know Your Customer, Anti Money Laundering, and Document Management System integration points. Our ideas include adding analytic tools for tracking suppliers' behavior and using AI to improve the automated workflow as the onboarding is one of the biggest challenges in SCF*". AI improves the efficiency and effectiveness of such activities by streamlining and making automatic some repetitive and long tasks, in addition to being challenging to suppliers.

Finally, AI plays a significant role in streamlining operations in the ***Routinising*** sub-phase*,* in which the SCF solution has been adopted and operational activities are carried out.

According to case studies, AI mainly supports the *automation of administrative procedures*. Among them, invoice reconciliation is the process of matching bank statements with invoices and can be automated thanks to AI. Moreover, Company G leverages AI in running the so-called "cash reconciliation", i.e., matching payables and receivables with the actual payment, migrating from manual to automated processes. Similarly, Company J explained that for specific solutions, such as *Dynamic Discounting*, it is imperative to accelerate the invoice reconciliation process because it also extends the period in which an invoice can be advanced, allowing the supplier to obtain liquidity in a shorter time—the buyer to obtain a higher discount rate. In turn, the main benefit from the automation of administrative procedures is the improvement in the SCF solution: AI in the SCF innovation process is generating additional opportunities for buyers and suppliers, coming from process compliance and speed, and turning a contribution to an increased value proposition of SCF, coherently with the results by van Hoek et al. (2022).

Beyond the automation of some process activities, AI can also provide *monitoring* and *improvement* features, offering suggestions to improve the day-to-day working activities of the buyer firm's employees responsible for the SCF process. For example, Company B stated that their platform analyses the throughput time of the process, allowing them to set targets about the completion time of the activities and shows if the performance is not in line with the objective. Moreover, AI provides suggestions for improvement based on the client and Company B's data. In the solutions provided by Company J, if a supplier sends several invoices with always the same type of error at the time of a new instance, the AI engine immediately suggests to the operator how others had successfully solved the issue in the past. Even Company A uses AI to streamline and better perform day-to-day activities: it provides virtual assistants to buyers and suppliers, who daily use the chatbot to solve common issues or ask questions, and thanks to the learning capabilities of AI, the platform becomes more powerful and user-friendly. This is a strong advancement for efficiency improvement, but it also leads to potential issues when technology fails. As highlighted by informant of Company A, sometimes chatbots fail, as well as machine learning tools. Mogaji and Nguyen (2022) have highlighted the importance of not overrely in AI for automation, as it can be a potential pitfall for productivity. The technology is designed to increase effectiveness and efficiency, but extreme attention should be paid to the outcome with human oversight to achieve it. (Chen and See 2020).

Another relevant finding is the AI support for *early payment decisions* within a *Dynamic Discounting* solution, i.e., defining whether to pay a specific invoice in advance and determining the appropriate discount. Company I confirms that AI helps determine an optimal invoice discount. Instead, Company A relies on a marketplace system, where suppliers can propose their desired payment terms and offer discounts. In this solution, machine learning can help the buyer optimize the available cash allocation to fund early payments by first serving the suppliers who offer the highest discount.

Finally, *fraud detection* is performed once the SCF solution goes live in this sub-phase. Company G checks that invoices are not duplicated on the platform, and there is continuous control if there is any misalignment from historical data: "*We can check that invoices are not duplicated through the platform, and we check inconsistent behavior. If something is abnormal according to historical data, we ask questions and block the supplier*". AI is also a risk management lever in this stage of the innovation process.

5.2 Benefits from the adoption of AI in the SCF innovation process

The categories identified for the benefits are Faster Processes, Cost Savings, Risk Reduction, and Enhanced Services, deducted from the literature review and confirmed with our findings. The benefits described by the respondents are quoted in Table 6. Based on previous literature, the benefits are then described and discussed for each category.

Faster processes Several benefits are related to the increased efficiency in the SCF innovation process in terms of time. Firstly, AI enables a faster *application assessment* of the buyer at the very first approach with the SCF provider. This benefits buyer who can get immediate feedback about their applications and SCF providers who can increase the number of applications processed, thus making their business more scalable by assessing credit requests faster.

Then, considering the buyer and its suppliers, AI could dramatically *speed up the onboarding* activity, thus benefiting both actors. The future aim of Company J is to apply AI to assess the suppliers' characteristics better and consequently propose convincing solutions, reducing the time to onboard new suppliers.

SCF providers enable companies to get *financing faster* because AI automates several activities, such as rapidly matching the account payables and receivables with the actual payments. Once the buyer has been accepted in the SCF program and the suppliers have been onboarded, AI allows the provision of cash to these actors immediately. A significant efficiency gain generally comes from *faster administrative procedures* for buyers and suppliers, in line with Rana and Daultani (2023).

Overall, AI can drastically increase the speed of the activities throughout the SCF innovation process.

Cost savings The introduction of AI allows suppliers to get *lower financing costs*. Indeed, advanced AI techniques better evaluate the buyer's credit risk, leading to a lower risk perceived by the investors and, consequently, lower interest rates required. Moreover, AI also expands the time window for early payment requests in the Dynamic Discounting solution, leading to a decrease in higher purchase cost savings for the buyer company.

Furthermore, buyers and suppliers adopting SCF solutions supported by AI are facilitated in the administrative procedures, thus enabling savings in human labour and jobs redesign oriented to more *value-added activities*. SCF providers reported that AI allows them to increase the efficiency of their core activities by automating portions of the process. They expressed general statements about an overall cost reduction for running the business.

Risk reduction Company B leverages AI to monitor supply chain transactions, thus allowing *the detection of fraud* and unethical behaviours. The service is provided to buyers and suppliers, enabling the detection of *internal* issues and discouraging misconduct. From the SCF providers' viewpoint, fighting against fraud and criminal activities is the main benefit AI enables regarding risk reduction. These risks are perceived as *external* by the SCF provider. They can be quite diversified, addressing legal risks, phishing attacks, or the hypothesis of collusion between the buyer and the supplier. The main benefit of AI is the enhanced efficiency of fraud detection in SCF, thanks to a higher detection precision rate and a higher speed in the computation time.

Furthermore, AI increases the ability to *forecast cash scenarios*. Company I particularly stressed this concept, as AI provides enhanced forecasting abilities. More specifically, accurately forecasting payment delays allows buyers and suppliers to manage cash shortage risks properly.

AI also increases the *objectivity of credit assessment*, impacting both SCF providers and buyers. Indeed, Company H provides ratings based on AI techniques, drastically adding value to their activities by enhancing the objectivity of their evaluations. The buyer firm also benefits from the increased accuracy, as the proper credit risk assessment leads to a lower financing cost. According to case studies, credit risk information about the supply base can be leveraged to understand the most suitable suppliers to target for an SCF solution.

Enhanced services AI improves *personalization and user-friendliness*. Company A stated that AI made their platform more accessible, functional, and user-friendly. They also provide a high volume of information about the involved players, customizing the service thanks to AI's learning abilities. Furthermore, through the automatic mapping of the supply base, a well-established buyer *can onboard* a broader

Table 6 Quotes from case studies – Benefits

Benefits
Faster processes
Faster financing: “We were used to 90-day invoice payment terms. That is not sustainable for a small business, as we are. Fortunately, our client offered us this AI-based program through Provider A’s platform, and we decided to give Provider A a try. It is incredible, but it took less than a week for the payment, really a couple of days.” – Supplier firm describing the AI-based SCF solution of Company A
Faster financing: “The platform allows the company to analyze the process from an efficiency point of view: how efficient are the processes in your company? If the throughput time of a process is 20 days in your company, and the other companies using the same platform are under 12 h, the platform suggests to you how to improve your company’s processes, based on the set objectives.” – Company B
Faster application’s assessment and **Faster supplier’s onboarding**: "Clearly the main benefits are related to the higher possibilities that a company has in terms of eligibility checks and onboarding, getting the answer in a few days rather than in weeks or months." – Company C
Faster administrative procedures: “This is a good tool, as it enables the so-called massive EDI: our customers want that all their suppliers send invoices automatically by EDI. If you have a tool that automatically programs your mapping script, you are going to have benefits in terms of time.” – Company D
Faster financing: “We enabled them [i.e., buyer and supplier] a financing in 5 min after the invoice is issued in the ERP of the supplier.” – Company E
Faster supplier’s onboarding: "Thanks to AI, we can onboard the new client, which is the invoice seller, times and times faster than banks. So thanks to this we can work very quickly, and this is very important in this type of business especially when you are onboarding a new client." – Company F
Faster financing: “The suppliers are in a situation where the needs of financing or the problems related to a specific purchasing category are spotted in a preventive way by the buyer. So, the buyer can help the suppliers in advance, thanks to AI. This would surely allow us to be more convincing in proposing our solutions. Therefore, the benefit for the buyer and the suppliers is a more efficient.” – Company J
Faster financing: “With this platform, the administrative process is greatly sped up, especially when there is a problem – and there are always problems” – Supplier firm describing the AI-based SCF solution of Company J
Cost savings
Non-value-added activities reduction: “For big suppliers, you can start a project and do the mapping manually. For smaller suppliers it is not profitable because the number of invoices is very high. Usually, the buyer firm does not spend money and resources in mapping small suppliers, even if they are the majority in the supply base. It could take months to connect suppliers, and mapping them manually is not profitable. So, the buyer firm needs to map the files and documents automatically, and Artificial Intelligence is very supportive.” – Company D
Non-value-added activities reduction: “AI can automate and reduce the human and manual intervention of back office, so fewer people work in no-value-added activities, that means a higher profitability.” – Company G
Non-value-added activities reduction: “The added value compared to traditional methods is the time saving. While traditional methods are paper-based, manual, and time-consuming, Artificial Intelligence allows to automate chunks of process and make them easily scalable, much more efficient.” – Company H
Non-value-added activities reduction: “Our AI engine becomes pervasive within the platform; the goal is to reduce administrative tasks to zero. It’s stupid to do administrative tasks on objects that are already coded and have many data: what is the value of a person? That person can do a lot of much smarter things. So, we try to make the user understand that the task he used to do manually can be done by a machine, while he can go on to more interesting tasks.” – Company
Lower financing cost: “Thanks to AI, the buyer can better appreciate the risk behind credit, and make a price that is competitive with other forms of financing offered to the supplier.” – Company J
Lower financing cost: “Turning back, I would have selected invoice financing and Company F earlier in our journey to help with cash flow and financing our supply chain partners, thanks to the flexible pricing, that turned out to be the best on the market.” – Buyer firm describing the AI-based SCF solution of Company F
Risk reduction
Fraud detection: “We have the spend guard, which allows us to analyze all the company transactions, both with suppliers and employees. The spend guard checks expense notes, orders, and invoices initiated by an employee, and the artificial intelligence understands if there are suspicious behaviors, reporting them to those in charge.” – Company B
Fraud detection: “One of the major gains is the fraud risk management, for sure” – Company C
Fraud detection: “We experiment with real practical applications of AI within the trade finance and supply chain space with the solutions by Company C. An example of the gains we had is around compliance, as Artificial intelligence is very good at detecting anomalies in documents and transactions.” – Buyer firm describing the AI-based SCF solution of Company C
Fraud detection: “AI is essential to combat against fraudulent transactions, terrorist transactions, criminal activities.”—Company E
Fraud detection: “AI helps us to mitigate different risks. In any invoice financing solution, risk management is an issue. A significant effort goes to eliminate risks, analyze risks, and AI enables us to mitigate fraud risks, exclude collaboration between the seller and the buyer and mitigate the legal risks. Moreover, we are also quite frequently violated by phishing attacks.” – Company F

Table 6 (continued)

Benefits
Improvement in cash forecasting: "The players in the supply chain, and the SCF providers as well, are exposed to many different risks, and there are several technologies to deal with the different risks. Again, some risks are more quantitative. Other kinds of risk can be assessed through qualitative data. AI helps us to deal with risk, to measure and mitigate risk. A practical example could be the prediction of payment delays and the forecast of cash flows." – Company I
Improvement in cash forecasting: "Artificial Intelligence in SCF solutions can really transform and enhance the receivables risk management." – Webinar of Company I with an SCF expert
Enhanced services
Improved personalization and user-friendliness: "With AI, we increment and accelerate the development of our solutions with really cool personalization, incrementing the friendliness of our solutions for both the buyer and the supplier." – Company A
Better understand of customers' needs: "Thanks to the chatbots, we are also able to provide answers to our people working on projects with customers, supporting our team in better running the every-day activities, turning to a better service level for our customers." – Company A
Increased objectivity in credit evaluation: "Certainly the biggest benefit of AI, especially in the trade credit context, is the ability to identify patterns in the data, which are difficult to be identified by humans. Because of the greater amount of data available, there is a certain level of objectivity even in the statistics, as the data set is huge. AI gives access to more data, and this data can be used in algorithms to provide better services." – Company C
Increased objectivity in credit evaluation: "It enables us to analyze their credit situation better." – Company F
Increased objectivity in credit evaluation: "Traditional methods are not fully objective because of the human in the loop: the human person does not always handle similar processes in the same way. AI maintains objectivity and accuracy of credit assessments that you would not have otherwise." – Company H
Better understand of customers' needs and **Opportunity to onboard a higher number of suppliers**: "Thanks to our AI engine, we can identify the supplier in need of SCF, identifying the invoices that the supplier is willing to finance, support the creditworthiness analysis and the buyer decision on a much more expanded set of information. Artificial intelligence application reasoning has a huge value for the tale suppliers that are so many and with small amounts: in these cases, the data is everything and the buyer just has to make reasoning about the processed data. The onboarding of new suppliers is highly benefitted from that." – Company J
Better understand of customers' needs: "Provider J's solutions are highly evolved in automatic payment management, also providing additional services through a modern solution set, being adaptable to the need of the supply chain, and compelling vision of the entire process." – Industry-specific report reviewing advanced SCF solutions

range of suppliers, which can be quickly onboarded. It is especially beneficial for small suppliers, as AI allows them to onboard SMEs efficiently and profitably despite the low number of invoices exchanged.

SCF providers can also achieve a significant gain by enlarging their front office capacity thanks to the adoption of AI in the different SCF solutions, which is in line with the reasonings of Fu and Zhu (2016) and Hung et al. (2020). Company H depicts a significant relief in their front office activities from adopting chatbots in the front-end relationship with companies.

AI is also beneficial in *better understanding customers' needs*, playing a pivotal role for SCF providers in providing their clients with consistent solutions to specific problems. Company G explains how AI allows them to properly analyze and better understand data, offering tailored services to their customers. This feature ended up with differentiation benefits for Company G.

5.3 Challenges from the adoption of AI in the SCF innovation process

The categories identified for the challenges are *Change management*, *Lack of Collaboration*, *Investment*, *Data Management,* and *AI Limitations,* deducted from the literature review and confirmed with our findings. The only exception is AI limitations, which have emerged inductively from the interviews. Variables are quoted in Table 7, explained in this section, and discussed in light of previous knowledge.

Change management Changing current processes represents one of the main hurdles to overcome for both buyers and suppliers. Company B described how the processes of its clients are just locally optimized. Implementing advanced technologies in processes characterized by substantial deficiencies needs to be improved. Thus, it can represent a barrier to AI techniques. Furthermore, buyers and suppliers must rely on *adequate technology infrastructure*, preventing the proper adoption of AI through the processes.

In addition to the struggles of changing current processes, case studies show that companies still perceive AI as something unknown and risky, as a *black box*. The "black box problem" (Li et al. 2018; Priore et al. 2019) refers to the underlying complexity of AI: it does not provide the user with a clear understanding of how inputs are managed and transformed into outputs. This needs to be more appreciated by buyers, thus leading to mistrust and suspicion towards the technology. Suppliers also have to understand the potential

Table 7 Quotes from case studies – Challenges

Challenges
Change management
IT infrastructure adjustment: "Today, companies have a million challenges that they do not even realize because they are still working with tools that are from two IT-eras ago, with tools that are still separate from each other." – Company B
Process adjustment: "It is crazy they only look at their specific little piece of the process, and they see it optimized, optimized from A to B, but they do not look from B to Z" – Company B
Low awareness about AI: "The challenge is that people want to understand exactly how it works, people stressing it, and maybe they want to try on a small project before the adoption, so this is an important challenge." – Company G
Low awareness about AI: "From our point of view, the main challenge is that artificial intelligence scares companies, so you must constantly open the black box. Nobody likes black boxes, and so bringing transparency to automated processes is key." – Company H
Process adjustment and **IT infrastructure adjustment**: "The challenge on the other side is to change the modus operandi that has characterized the industry for decades. Some companies are still using paper invoices, for them, it is hard to adapt their procedures to digital innovation. This is not just related to artificial intelligence, it's a challenge of digitizing the process, especially for SMEs." – Company H
Low awareness about AI: "Let us say that we try to 'hide' AI. If you go to a client and you start talking about Artificial Intelligence, he thinks it's complicated. So, I don't talk to the client about AI. Then, when we do a demonstration of the platform, the client asks me for technical explanation, I open the black box of AI and explain the rationale behind AI." – Company J
Low awareness about AI: "We started the implementation of the solution a while ago with company J, but no one has yet provided us with precise guidance or some sort of tutorial. If I don't know how this solution works, how can I trust it?" – Supplier firm describing the AI-based SCF solution of Company J
Lack of collaboration
Low data sharing: "There are some challenges in gathering data from certain sources; for example, in some countries, there are problems. They are not transparent and do not share the data, this is a problem because you are not able to evaluate the transactions properly."—Company E
Low data sharing: "Talking about AI, today it's important to have clients willing to share their data and to collaborate in the initial stage because without data you cannot do so much with AI." – Company G
Low data sharing: "We are having some problems with artificial intelligence, especially when it comes to data sharing. In fact, some clients do not want to share their data unless we anonymize it and we make it completely filled, so there are some legal aspects to address before actually starting the collaboration with a client." – Company G
Investment
Need for a short ROI: "The goal of companies is to make money: they cannot afford to make intense research about advanced AI, they require a very fast ROI for every investment." – Company D
High investment cost: "AI techniques are quite expensive to implement, this is because there is a problem of knowledge, training costs are high." – Company E
Data management
Data availability and maintenance: "The main challenge is having the data available. Obviously, machine learning exists, and it's not new, but the problem is having the big data to feed the algorithm. We gather this data leveraging on the community of companies accessing our services in the platform, it is a data lake coming from the companies themselves. We have a multi-tenant software-as-a-service, and the 97% of our customers authorize to pool their data, albeit in an anonymous and aggregated way." – Company B
Data significance: "In terms of disadvantages, AI techniques need a large number of observations available to work, so there is a big limitation: companies want to adopt these techniques prematurely. They must understand whether the available dataset represents the population of suppliers they are targeting. This is a big risk: especially when you set up automatic decision systems, the risk is to develop models based on a few hundreds of default observations, then making crazy mistakes because the dataset was not representative of the real situation." – Company C
Data availability and maintenance: "Banks offer different formats to the buyer companies and suppliers. Each bank performs the same procedure in a different way from the other banks. When we receive the bank account statements from a new applicant, it takes much time to get these statements in one format that could be readable from our solutions." – Company F
Data security: "It's important to isolate SCF-related information because corporates have information about invoices so payables, receivables but also the payments, you need to have all the data in the database. All these data have issues of confidentiality and security." – Company G
Data availability and maintenance: "A big challenge with any AI project is gathering data, as companies either do not have data or data are messy. In all our projects, and typically in most data science projects, we spend much more time on cleaning the data than in the algorithm itself." – Company I
Data availability and maintenance and **Data security**: "Data availability and security are challenging. Coming from the banking world, we get a customer who only brings us part of their invoices, but they would rather have 3 or 4 brokers managing their invoices, so we miss the complete overview on the process." – Company J

Table 7 (continued)

Challenges
AI limitations
AI errors: “Chatbots provided by technology providers sometimes are wrong and make mistakes. Technology still needs to be improved.” – Company A
AI errors: “Sometimes machine learning tools get wrong and make errors.” – Company A
AI errors: “Clearly the disadvantages are related to the fact that machines and models by definition lead to errors” – Company C
Difficult identification of application areas: "In developing a new AI-based solution for SCF, it is not that easy to understand a promising application field that would make the life of the supply chain easier. It’s hard to understand how AI can support cash flows management." – Company G

of using AI in SCF solutions as it can be a lever to boost efficiency, as well as transparency and visibility in the buyer–supplier relationship. Indeed, the lack of these two elements is often reported as a primary barrier to the adoption of SCF programs.

Lack of collaboration The main challenge from the cases is undoubtedly the *low willingness to share data* (de Campos Martins and Simon 2018). Both buyers and suppliers are reluctant to share data, but without data, the AI engine cannot be properly powered. Company E described disclosure issues in countries that do not allow the sharing of data. Company J explained that suppliers often prefer asking different banks for an invoice discount, interacting with several players, and providing them only partial visibility of their company. The low willingness to share data turns out to be a challenge for SCF providers as well. To overcome this issue, they can leverage the concept of community. Based on its experience, Company B stated how SCF providers should leverage strong communities to gather data: being part of a community should bring several advantages to buyers and suppliers, provided they give their consensus to data sharing. Although community members usually give their consensus to share data anonymously and aggregated, it is enough to generate value-adding analysis with AI.

Data management A common issue in case studies is the need for more capability of both buyers and suppliers to manage data correctly. Even if they decide to share their data, such data could be useless since they are messy and redundant. This problem is also a challenge for SCF providers. For example, Company I highlighted how the time spent on data cleaning is much more than the one dedicated to algorithm development in most AI projects. Then, the *data quality* needs to be *maintained* over time (Arunachalam et al. 2018; Singh et al. 2019).

Moreover, getting a *representative dataset* is also a challenge: even if SCF providers can get a significant volume of data, the dataset cannot represent the market population. Although the dataset is large enough, some crucial elements of the phenomenon under scrutiny are not considered. Company C stated that firms adopt AI techniques prematurely, leading to unreliable models and wrong decisions. Then, *data security* is a genuine concern, as described by Company G. Once they have the consensus to manage the data within their platforms, they must make an effort to keep such data secure, avoiding hacking attacks or cybersecurity issues.

Investment Company E mentioned the *investment costs* required to implement the AI solution in the platform as a relevant challenge. Indeed, most of the costs are related to training because there is a lack of knowledge of AI techniques. Company D is a start-up that pointed out a specific challenge related to young companies providing AI-based services: young companies often need help to afford deep research about advanced AI techniques simply because they necessitate getting *returns on investments (ROI)* faster than established players. Still, one of the main problems for providers is the need for more models and tools to calculate the precise ROI of using AI in SCF programs, making the decision to integrate such technology in the current use of SCF programs more questionable.

AI limitations Some intrinsic features of AI might prevent its spread in SCF programs, as AI still makes *errors* that are hard to eliminate. Even if AI can outperform humans in some situations, it must improve. Virtual assistants can fail and make trivial errors, which a human would not have done. Moreover, Company C stated that an expert analyst with the time to analyze a new company accurately, interact with the owners, and evaluate the expected credit risk currently wins against the algorithm. The challenge is enhancing AI accuracy, but vast amounts of data are required, and collecting them takes a long time. Company G also highlights the problem of *identifying a promising application area* for AI, affecting only the SCF providers. The issue at stake is the complexity of defining the most convenient area in which AI should be developed. Company G illustrated the possible applications of AI, such as improving the user experience for the platform users or reducing fraud. Estimating the expected profits accurately is still hard, leading to difficulties in prioritizing investments.

6 Discussion

In this section, our results are discussed in the light of the received literature. In doing so, we follow the same structure of the results section, critically discussing the role of AI in the SCF innovation process and then the benefits and the challenges stemming from AI adoption.

6.1 AI in the SCF innovation process

Following the model by Wuttke et al. (2013b), our results show that AI significantly impacts the activities and decisions conducted within the SCF innovation process in both the initiation and implementation phases. Still, there is no evidence of AI supporting the activities in the *Restructuring* and *Clarifying* sub-phases since these are relational activities, not helped by the use of a technology.

6.2 Initiation phase

Within the *initiation phase* of the SCF innovation process, Wuttke et al. (2013b) suggest the buyer firm as the innovator, playing a more decisive role than a provider of innovative products in its purpose of setting an SCF solution with the supplier. Thus, given the complexity for the buyer firm, the SCF provider becomes an essential catalyst in the SCF innovation process (Jia et al. 2020b). We discovered that the contribution of AI in setting the SCF agenda is twofold. First, AI can support the analysis of a buyer firm's supply base (Lorentz et al. 2020) to identify the most suitable SCF solution. Indeed, AI allows to profile and better evaluate suppliers according to pre-set characteristics and identify their financial needs. Second, AI has great potential in predictive analysis regarding future cash flow (Badakhshan et al. 2020), predicting the needs of the buyer and its suppliers, and offering new solutions and services based on that. According to these results, we formulate the following propositions:

P1: AI helps the buyer forecast the cash flows between buyer and supplier through predictive analytics.
P2: AI helps the SCF providers profile buyers' needs, offering new SCF solutions and related services (e.g., insurance, risk assessment, etc).

After the *Agenda setting*, our results show that AI primarily supports the SCF provider in the *Matching* phase, especially in *proposing* the buyer firm *the most proper solution* and in assessing the risks related to the different financial transactions. Structured and unstructured data are collected and analyzed, unlocking insights into the cash flows in the supply chain, the past transactions between buyers and suppliers, and other relational aspects. This data feeds machine learning algorithms to understand the actual needs of the buyer firm in managing cash flows with suppliers (Badakhshan et al. 2020). Thus, the matching is optimized and runs quicker than the traditional matching performed by banks, ideally by selecting more than one solution jointly (Guida et al. 2021; Gelsomino et al. 2019). A solution proposal has yet to be mentioned in the existing literature. An effort in this direction can be recognized by Guida et al. (2021), proposing a scheme for selecting the most appropriate SCF solution based on the characteristics of the buyer–supplier relationship. However, in this research, no emphasis is given to digital tools supporting the decision, such as AI. Then, despite demonstrating low support of AI for complex transactions, Olan et al. (2022) claim the importance of AI in suggesting the complexity of the issues in the supply chain and the identification of alternative SCF solutions. Thus, our contribution overcomes one of the significant gaps in the SCF body of knowledge, such as the possibility of simultaneously adopting different solutions in different parts of the supply chain based on AI-based and informed decisions.

AI proved highly beneficial for *risk management* (Ivanov 2021). According to Jia et al. (2020a, b), many factors concur in the SCF credit-related issues, such as creditworthy estimations, supplier credit, payment history, and bankruptcy. Credit-related factors can strongly affect the information system behind the SCF solution. The massive amount of data from the buyer and its suppliers promotes the establishment of a solution to track and enhance the relevant information, especially for low-creditworthy suppliers (Liebl et al. 2016). In this direction, a stream of literature presents the application of machine learning techniques supporting credit risk assessment (Khashman 2011; Zhu et al. 2016, 2017, 2019; Song et al. 2021). In addition, our cases have given empirical evidence that SCF providers leverage AI to *assess the buyer's credit rating*, *define the credit limit*, and *detect fraud*. Companies can work with structured and unstructured data from different sources (i.e., balance sheets, transactional data, websites, reports, etc.) to get the most out of the SCF solution, as Song et al. (2021) indicated.

Based on the new results related to the Matching phase, we propose our third proposition:

P3: AI allows the integration of multiple structured and unstructured data from different sources (i.e., transactional information, financial and economic information, external information from the web and documents) to assess the buyer's related risks better and define the potential scope of the SCF solution (i.e., eligible suppliers, credit limit).

6.3 Implementation phase

In this phase, the SCF solution has been chosen, and all the activities to set it up are needed. AI allows the process to be streamlined and helps in several activities.

According to the results of Aksoy and Öztürk (2011), AI is helpful in clustering and selecting suppliers to offer them an SCF solution. Despite their research being oriented towards the selection of suppliers in the just-in-time (JIT) context, we extend such contribution to the SCF domain. We find that AI can significantly support the *supplier categorization* activity within the *Redefining* sub-phase, which is critical to identifying the most suitable suppliers to be involved in the SCF solution. Moreover, once the suppliers are identified, AI allows the bolstering of several needed activities: the pricing of the SCF solution and risk management practices, such as the credit rating calculation of the involved suppliers and the detection of fraud. The categorization of suppliers opens the possibility of setting different prices according to classes. According to de Goeij et al. (2021), the outcome of this activity is beyond important as pricing is the first element a vendor looks at when deciding whether to join the SCF solution. Thus, AI helps create more complex decision models that consider more attributes than could be done without technology, providing additional levers for understanding which suppliers to engage and at what price.

We find risk analyses and risk management practices among the activities most impacted by AI in this phase. Results show that AI supports the *supplier's credit rating assessment* and *credit limit definition.* Such analyses are the same that are performed to assess the buyer's creditworthiness in the *Matching phase*. Although most SCF solutions are based on the buyer firm's credit rating, the supplier's credit rating is crucial in optimizing the collaborative cash cycle (de Boer et al. 2015). The SCF provider can determine the SCF solution's optimal features that outperform a buyer-only perspective by taking a supply chain perspective. According to case studies, AI is highly supportive in collecting and leveraging data about the differences in capital cost between members in the chain, then projecting and proposing the best SCF solution.

Moreover, AI is used to combine different sources of information to assess suppliers' credit risk better and to detect potential suppliers' fraud. Extant literature matches these capabilities enabled by AI: According to Song et al. (2021), analysing the financial and operational data of the focal firm increases the ability to raise funds for upstream players. Thus, AI-based analyses enable suppliers to raise funds based on their performance and the financial qualities of their customers.

As explained above, the activities performed during this sub-phase are similar to the ones of the matching phase but now with the suppliers' perspective. Thus, we formulate the fourth proposition:

P4: AI allows the integration of multiple structured and unstructured data from different sources (i.e., transactional information, financial and economic information, external information from the web and documents) to assess the suppliers' related risks better and define the actual scope of the SCF solution (i.e., suppliers to involve, dynamic pricing of the solution).

In the *Disseminating* sub-phase, AI helps in one of the most time-consuming activities in the SCF innovation process: *suppliers' onboarding*. It includes all the activities of suppliers' training, engagement, and involvement, including standard bureaucratic activities, such as the *Know Your Customer* and *Anti Money Laundering* analyses. Despite being an under-investigated topic in the literature, suppliers' onboarding is a crucial issue, as misconduct or poor management of these activities leads to suppliers' reluctance to adopt SCF solutions. Banerjee et al. (2021) described this critical issue and were the first to study the use of digital technologies for supplier onboarding in Reverse Factoring solutions. However, they did not study the role of AI. Instead, we find that AI streamlines these activities using different techniques. For instance, chatbots are used to train and engage suppliers in the platform. In general terms, AI supports buyers who want to automate and digitize most of the suppliers' onboarding activities, making them more efficient. Especially when targeting SMEs, SCF solutions that include digitalization or platforms must ensure easy onboarding and limited—or null—investment in technology and transaction handling (Goeij et al. 2021). In this direction, using AI to disseminate the validity of SCF among supplier firms may be a promising development. For this reason, we formulate the fifth proposition:

P5: Suppliers' onboarding activities are streamlined thanks to virtual assistants that help suppliers understand how to use the solution and adequately provide all the information to perform the onboarding activities, such as Know Your Customer or Anti Money Laundering.

In the *Routinising* sub-phase, the last stage of the Implementation phase, the technology helps streamline and automate various administrative and ordinary management tasks of SCF solutions. As highlighted by van Hoek et al. (2022), Robotic Process Automation is deployed to conduct the everyday and repetitive administrative tasks of the procurement process, which can be found in the supply phase (Guida et al. 2023). Similarly, we find that AI performs an automatic invoice reconciliation through image recognition that pairs documents, such as the purchase order, the bill of lading, and the invoice. Technology makes the process more efficient and effective as mistakes decrease by digitizing and being supported by AI. The technology can also identify any issues that could arise from a careful reading of the data, enabling a continuous process of monitoring and improvement of the SCF solution, also leading to the identification of misconduct by suppliers who send false invoices to get access to early payments. If the values in the documents do not match, the technology sends a warning signal. This result aligns with the research by Zhou et al. (2020), who developed a model to identify fraudulent supplier behavior associated with financing transactions.

Based on the abovementioned results, we propose the following propositions:

P6: AI helps in automating administrative and manual activities, such as invoice reconciliation, thanks to RPA that automatically matches invoices, orders, and payments, and thanks to virtual assistants, such as chatbots, that help operators manage the SCF solution.

6.4 Benefits of AI adoption in the SCF innovation process

The study's results have identified four benefits stemming from AI adoption: *faster processes*, *cost savings, risk reduction,* and *enhanced services.*

The first positive effect of AI is on processes speeded up through automation and digitization. Faster onboarding and faster reconciliation of documents are crucial to increasing the utilization of SCF solutions and providing the supplier with a larger time window in which they can request an advanced payment. This benefit is critical for SCF solutions, as highlighted by research in the field. Since the first conceptual formulations of SCF, the duration of financing or the timing of the SCF solution have been described as fundamental dimensions for working capital financing. Pfohl and Gomm (2009) introduce the time dimension among the fundamental levers of SCF. More recently, de Goeij et al. (2021) focus on the time to access the financing and the time to assess an SCF solution, describing how a supplier's trust in the buyer is affected by the high payment term extension and the long invoice approval time in reverse factoring, which the supplier negatively perceives. Caniato et al. (2016) assert a significant time investment on the buyer and supplier side, especially when not including digitalization or the use of platforms. In this direction, introducing AI-based solutions to support the SCF innovation process solves many inefficiency problems. According to Jia et al. (2020a), advanced analytics techniques allow the SCF provider also to increase the flexibility of the whole SCF scheme and respond timely to the needs of buyers and suppliers involved in the SCF solution, in line with the results we have achieved.

According to the results, we formulate the following proposition:

P7: The buyer and its suppliers benefit from AI as it allows faster financing, thanks to the reduction of non-value-added activities.

Reducing non-value-added activities and making the process efficient also lead to *cost savings.* Furthermore, AI reduces the financing costs related to SCF solutions, which is a substantial benefit, especially for suppliers who generally pay them. As explained in Sect. 5.1, AI allows the development of models to evaluate both the buyer and suppliers by integrating sources of structured and unstructured data, involving a better evaluation of the buyer's and suppliers' creditworthiness, impacting the pricing and costs of SCF solutions. The cost dimension of SCF solutions is a widely recognized issue (Wuttke et al. 2013a; Nguyen et al. 2018), and previous research attached high value to the information in the SCF pricing: it supports the decrease in investment risks and costs of financing projects within supply chains, and optimize financing (Gomm 2010; Pfohl and Gomm 2009). In this direction, leveraging the proper algorithms brings lower costs for buyers and suppliers, especially when suppliers are SMEs (Jia et al. 2020a, b; Yu et al. 2021). In the broader procurement domain, the time savings resulting from AI-enabled automation is more widely recognized: according to Gottge et al. (2020), the gain in process automation is enabled by IT support for data structuring, prioritizations, analysis and predictions, and automation of operative activities that reduce administrative tasks. van Hoek et al. (2022) describe the gains from the automation of existing processes that are already stable, freeing up resources to focus more on strategic priorities and projects.

Our study confirms most of the results coming from the abovementioned research, applying those concepts specifically to SCF solutions. Accordingly, we formulate our following proposition:

P8: AI allows automation of activities and improves risk assessment, thus reducing administrative and financing costs of SCF solutions.

AI enhances the *risk management* capability in managing the supply chain cash flow significantly when reducing the risk of manual operator decision-making or internal and external fraud. The argument was addressed in a recent study by Zhou et al. (2020). They explained that the AI engine is trained on a high amount of transactional data, with the aim of intelligently and automatically detecting fraudulent business deals, improving the accuracy and efficiency of anti-fraud, anti-money laundering, anti-bribery, and other aspects in the supply chain to a large extent. Then, the AI-based solution brings visibility to the central problem: an alarm will be raised in the risk management system if a financial fraud is identified. The suspicious business deal is then demanded to the manual decision. Our cases confirm this model, as SCF solutions providers use AI techniques, such as image recognition, to detect potential mistakes in SCF-related documents (e.g., purchase orders, invoices, etc.), detecting either potential mistakes given by human errors in the data entry, or fraud by suppliers. The main benefit is the precision of AI in detecting such errors or misconducts, leading to high efficiency and effectiveness. AI's precision is also recognized in the more objective assessment of buyers and suppliers. AI uses large datasets of historical data that could be impossible to manage otherwise. In addition, SCF providers in our sample use external sources of unstructured information from the internet to better monitor and evaluate suppliers. Our results add evidence to the research of Zhou et al. (2020), which describes a data mining algorithm for financial fraud detection in a supply chain. The applicants (i.e., the suppliers) are assessed and classified through many dimensions, such as credit history, credibility analysis, capacity to repay, cash flow ability, assets and liabilities, and corporate tax certificate. In this way, all the relevant information coming from different sources converges in the computation of the credit rating, turning to more precise and reliable indexes used for the assessment in the platform and the final decision of the human in the loop. As a result, we formulate the ninth proposition:

P9: AI reduces the risk of fraud and double financing thanks to the use of several sources of structured and unstructured data.

AI gives SCF providers an additional lever to enhance the service they offer. The technology is used to improve the experience of the buyer and its suppliers using AI, bringing together the customization of the service and very smart processes generally managed through AI-based platforms. Caniato et al. (2016) and Moretto and Caniato (2021) proposed a digital transformation of SCF solutions emphasizing the need for digital tools to manage operations. de Goeij et al. (2021) investigated the recent adoptions of reverse factoring based on a frictionless onboarding process for the supplier, thanks to the support of a digital SCF platform. We complement their research by providing evidence about using AI-built platforms, which conduct better customization and usability. Indeed, AI is used to better understand the customers' needs and recommend specific solutions to them, providing additional business opportunities. This result is in line with the contributions of Zhu et al. (2019) and Bousqaoui et al. (2017), which describe the increased business opportunity as the primary benefit of AI in SCF.

These digital features and personalization characteristics are no longer a nice-to-have for SCF, mainly thanks to the increasing deployment of working capital management solutions, leading to lower implementation costs and straightening the learning curve (de Goeij et al. 2021). Our case studies also add the AI component to reinforce further the importance of customizing and facilitating the onboarding of new companies in the SCF innovation process.

SCF providers can also achieve a significant gain by enlarging their front office capacity thanks to the adoption of AI in the different SCF solutions, which is in line with the reasonings of Fu and Zhu (2016) and Hung et al. (2020). Company H depicts a significant relief in their front office activities from adopting chatbots in the front-end relationship with companies.

6.5 Challenges of AI adoption in the SCF innovation process

The main challenges of implementing AI in SCF solutions are *change management, lack of collaboration, investment, data management,* and *AI limitations.*

Among the main issues that emerged from case studies, we find *change management*, which assumes a two-fold meaning in our study. First, firms have raised the criticality of changing processes to adapt them to AI. This barrier is well-recognized also in the reviewed literature. Gottge et al. (2020) address the management of technological changes in the automation of the procurement process, which is highly critical and resource-consuming for a new-adopter company. More specifically, in the domain of SCF, Jia et al. (2020a, b) claim that the change in the financial network structure transforms the traditional SCF activities, asking for the adjustment of processes, data sharing, and technological infrastructure. However, the need for standard processes remains a significant barrier to implementing digital technologies in PSM (Kache and Seuring 2017; Singh et al. 2019). Second, firms are also afraid to adopt AI as it is perceived to be new and unknown, and so as a potential risk. This confirms the results of the studies by Li et al. (2018) and Priore et al. (2019), who refer to this issue as the "black box problem".

Despite these issues, AI should be seen as a potential tool to improve the benefits of all the actors participating in the SCF solutions and to increase transparency and trust among players. This is extremely important for receivables financing solutions that deal with the buyer–supplier relationship. Banerjee et al. (2021) state that suppliers expect technologies to boost transparency and reduce variability in trading activities when adopting a digital reverse factoring solution. According to this research, trustworthiness is fundamental in SCF solutions, as suppliers are willing even to reject an attractive SCF offer when perceived as unfair (de Goeij et al. 2021).

This discussion links to the second barrier, the *lack of collaboration*, which is also recognized in the received literature. As emerged from the case studies, AI needs data to perform well, but players participating in SCF solutions are reluctant to share data (de Campos Martins and Simon 2018). According to Song et al. (2021), the SCF provider should proactively collect and utilize data coming from relational information. Indeed, sharing relational information fosters financial activity promotion and success. However, the supplier's reluctance to share data remains a significant hurdle (Banerjee et al. 2021). Thus, suppliers also must increase their awareness of AI and its potential benefits. This change in the paradigm of working jointly with technology support should be rooted in the mindset of employees who do not challenge the status quo (Flechsig et al. 2022). Building *trust and awareness* in AI is vital as employees' reservations on the buyer or supplier side pose a significant barrier to the implementation (Singh and Singh 2019).

Once data are shared, another challenge is represented by the capability of *managing the data*. Data management in AI must be intended to create seamless results through data processing and complex problem-solving, benefitting the company by leveraging the technology (Baryannis et al. 2019; Olan et al. 2022). From case studies, the main concerns regard the capability to have enough data of good quality and the capability of maintaining their safety. The lack of data availability and significance of data is well debated in the PSM literature and addressed as one of the significant hurdles harming the full implementation of AI (Kumar Dadsena and Pant 2023). One of the seminal works is the paper by Hazen et al. (2014), which deepens the understanding of data quality in supply chain management. According to Schoenherr and Speier-Pero (2015), one of the major barriers is the inability to grasp insights from available data, referred to as data significance in the case studies presented. Finally, our findings support the results regarding data security by Kache and Seuring (2017), as they look at the issue of cyber security at the company and supply chain level when implementing AI. Thus, with our results, we validate the data management challenge that has been raised in the PSM literature with empirical evidence, and we extend this issue to the SCF domain.

Another barrier concerns the significant *investments* needed to implement AI in SCF platforms. They are linked to the need to develop AI techniques specific to SCF, which is expensive, and the difficulty of calculating the return on investment. This aspect is crucial: the need for investments to change the IT infrastructures is referred to as a heavy barrier in many recent PSM studies (e.g., Bienhaus and Haddud 2018; Gottge et al. 2020). According to Flechsig et al. (2022), companies often refrain from investments because it is simply a matter of costs. They are unaware of the benefits they can get, even looking at the subsidies from government initiatives supporting digitalization projects and the adoption of SCF. However, the efficiency of supply chain financial services can be significantly promoted through digital technology if more rigorous investment decision-making processes are conducted (Zhou et al. 2020).

Finally, *AI has limitations* we have identified in our research; not all of them are known in the literature. AI is only sometimes reliable, as expressed by many firms. AI is a support, but humans can make better decisions in particular circumstances. Moreover, AI must be trained with large datasets that are not always available. In line with this result, Flechsig et al. (2022) explained that the high number of different data formats, interfaces, and IT systems involved in the technology change leads to higher complexity to be handled by AI, resulting in higher error susceptibility. However, this issue is mainly highlighted by the companies in the sample and is not much reflected in the academic literature, which highlights the benefit of AI in reducing errors, and outperforming humans (e.g., Gottge et al. 2020; Toorajipour et al. 2021; van Hoek et al. 2022).

7 Conclusions

The main objective of the research was to investigate the role of AI in the SCF innovation process by studying its impact on the activities in the phases and sub-phases of the process, together with the resulting benefits and challenges, through ten case studies of SCF providers. The perspective in the study was threefold: the buyer, the supplier, and the SCF provider. The findings provide an original contribution to both research and practice and opportunities for further research. Bringing together practical experience and theoretical knowledge, as well as considering different perspectives, gave the results the proper level of validity and generalisability for scholars and practitioners who could benefit from a comprehensive overview of the role of AI in the SCF innovation process.

7.1 Theoretical implications

Analyzing the impact of AI on supply chain processes and decisions is essential to understand at which strategic level data have a more informative and supportive role (Chehbi-Gamoura et al. 2020; Toorajipour et al. 2021). AI can support the human decision-maker in strategic activities, solving more complex problems than traditional techniques (Min 2010). However, literature about the support of AI to the SCF innovation processes is still scarce, while actors belonging to the SCF ecosystem need tools to help them in the decision-making process (Guida et al. 2021). The exploratory research presented in this paper provides the first original contribution in this direction, participating in the general scientific debate about innovative applications of AI.

The main contribution is understanding the specific role of AI in the SCF innovation process and investigating which phases, sub-phases, and activities can be empowered and accelerated. We have identified several activities impacted by AI, jointly considering the main actors involved (i.e., buyer, supplier, SCF provider). In contrast, previous research in the SCF domain has primarily focused on one actor at a time, considering the buyer separately (e.g., Chen and Hu 2011; Wuttke et al. 2013b), the supplier (e.g., de Goeij et al. 2021), and the SCF provider (e.g., Jia et al. 2020a, b).

A structured framework and nine propositions have been formulated, significantly contributing to the existing knowledge on this subject. It enhances the theoretical value of the model proposed by Wuttke et al. (2013b), which serves as a reference point. To date, the SCF literature has primarily explored AI's contribution to credit risk assessment, yet this study brings attention to numerous other activities with substantial untapped potential. Furthermore, the three stakeholders have recognized the benefits and challenges of integrating AI into the SCF innovation process. Only a limited number of these have been previously addressed in the literature, often needing more specific references to SCF. Among the benefits recognized for AI in the PSM domain are the efficiency gained from process automation (Gottge et al. 2020), the reduction of non-value-added activities (van Hoek et al. 2022), and the risk management improvement (Badakhshan et al. 2020). The main challenges to implementing AI are mainly related to change management, low awareness of user companies (Flechsig et al. 2022), and weak data management and exploitation (Hazen et al. 2014). However, these main benefits and challenges had previously been placed in contexts other than the SCF, especially far from the SCF innovation process.

7.2 Managerial implications

This paper holds significant managerial value, as its primary findings contribute essential knowledge for practitioners engaged in the SCF innovation process. While AI is recognized as a pivotal innovation, practitioners often need more proper guidance regarding the most promising application areas, expected benefits, and challenges to overcome. Despite the recent surge in GenAI and the growing interest it has garnered from businesses, there remains a limited awareness among firms about AI's potential impact, as evidenced in our case studies and echoed in the literature (Bienhaus and Haddud 2018; Kache and Seuring 2017; Flechsig et al. 2022). Assessing its actual value is challenging, and cultural barriers persist concerning the willingness to share data to unlock the benefits of AI. Although SCF is gaining momentum, there is still a need to bridge the gap between AI's perceived and actual value within this context. SCF is gaining momentum, but there is still space for improvement, primarily through new technologies (Chen et al. 2021). Indeed, AI proved valuable in facilitating the supply chain's financial flows and mitigating the related risks. Remarkably, the activities required to implement an SCF solution are complex, and to obtain a valuable result, they require several analyses where a high volume of data should be processed. It is where the actual value of AI comes in.

This research demonstrates that the analysis run by AI outperforms traditional evaluations since more parameters and requirements can be included in the computations. From another angle, AI in SCF can also enhance the customer journey, enabling tailor-made services to support the client throughout the process and better understanding the customer's needs by monitoring the actual situation and forecasting future cash scenarios. Industrial players who are the clients of SCF providers (i.e., buyers and suppliers) can now better understand the essential activities in the process and figure out how AI can enhance them to make the best decisions for their financial supply chain. Buyers can better distinguish the different offerings with the final purpose of choosing the alternative that best fits their own corporate needs and objectives. Suppliers can realize that adopting AI in SCF can have several advantages, from increased objectivity of credit evaluation to selecting a solution that perfectly answers their needs, facilitating their onboarding process.

7.3 Limitations and further developments

This research bears some limitations that provide exciting opportunities for future research.

The first limitation pertains to the sample, which exclusively comprises SCF providers. While we address benefits and challenges related to buyer firms and their suppliers, these insights are gathered from the perspective of SCF providers. Our rationale behind this choice lies in the belief that SCF providers possess extensive experience dealing with numerous buyers and suppliers, affording them a comprehensive understanding of the pros and cons associated with AI adoption from the standpoint of both buyers and suppliers. However, conducting additional research from the perspective of buyers and suppliers could further complement and validate our findings. Another limitation of the present study is hidden in the choice of the SCF innovation process considered for reference from the literature: it holds the traditional buyer firm's perspective, in which a large buyer relies on an SCF provider to both improve its working capital and to support its supply base, adopting just payables financing solutions. Therefore, receivables financing solutions still offer exciting areas for further investigation.

AI is not adopted as a single technology in a firm's traditional processes. However, it is often adopted in a larger project of digital platforms that aims to improve several processes, including treasury, payment, finance, and purchasing processes. Generally, these platforms relate to many actors that offer different solutions and services, creating a large SCF ecosystem (Chen et al. 2022; Choi et al. 2023). Exploring the management of the SCF innovation process and AI adoption within shared ecosystems would be intriguing. Understanding how specific barriers, such as collaboration, data management, and data quality, which could theoretically be heightened in more extensive and diverse ecosystems, are effectively addressed in practice. Similarly, a new trend in SCF relates to multi-tier financing (Yoo et al. 2021), which implies the involvement of the suppliers of the buyer firm's suppliers in SCF programs. In this case, it would be relevant to understand how the SCF innovation process is managed and which benefits AI induces in solving/simplifying complex issues, such as managing an SCF solution from a multi-tier perspective.

To conclude, this research can be further developed by expanding its scope and shedding light on undiscovered insights at the intersection of AI and SCF.

Annex A

Table 8 description of SCF solutions—reported from Guida et al. (2021)

SCF solution (payables financing solutions)	Definition of the solution and description of the roles of the actors involved	Sources
Reverse Factoring	Reverse factoring is an SCF solution wherein a large buyer facilitates early payment of its trade credit obligations to the supplier. A factor purchases accounts receivables from suppliers whose buyers (generally an informationally transparent high-quality firm) guarantee that the payment will be fulfilled	Klapper, (2006), Van der Vliet et al. (2015)
Confirming	Confirming is a solution whereby the transferring debtor issues the factor with an authorization for payment to its suppliers, making this player the manager of trade payables. This solution usually contains a binding commitment regarding the availability and inclusion of recourse to the seller	SCF Observatory of Politecnico di Milano (2020)
Purchase Order Finance	Purchase order finance is a short-term commercial finance option that provides advance funding to suppliers for verified purchase orders. This financing can cover all the related working capital needs of the seller, including raw materials, wages, packing costs, and other pre-shipment expenses. The buyer issues its commitment to pay once the seller ships and makes available the required documents matching the purchase order and other stipulated conditions. Purchase order finance is intended as a pre-shipment financing solution	UN/CEFACT (2018), de Boer et al. (2015)
Credit Card	A virtual credit card (also known as a B2B or purchasing card) is an SCF solution that entails the use of a "virtual" credit card to streamline payments between the buyer and the supplier. The solution can be implemented by the supplier (supplier-centric paradigm) to streamline its cash flows related to its customer base in a solution that is quite similar to factoring. This solution can also be implemented by the buyer (buyer-centric paradigm) to steady its supply base, implementing a solution that is conceptually similar to reverse factoring. The latter paradigm is the most common and is the reference for the present study	Bonzani et al. (2018)
Dynamic Discounting	In a dynamic settlement of invoices, for every day of advance payment with respect to the commercial terms, the supplier grants to the buyer a discount on the invoice nominal value	Gelsomino et al. (2016)

Annex B

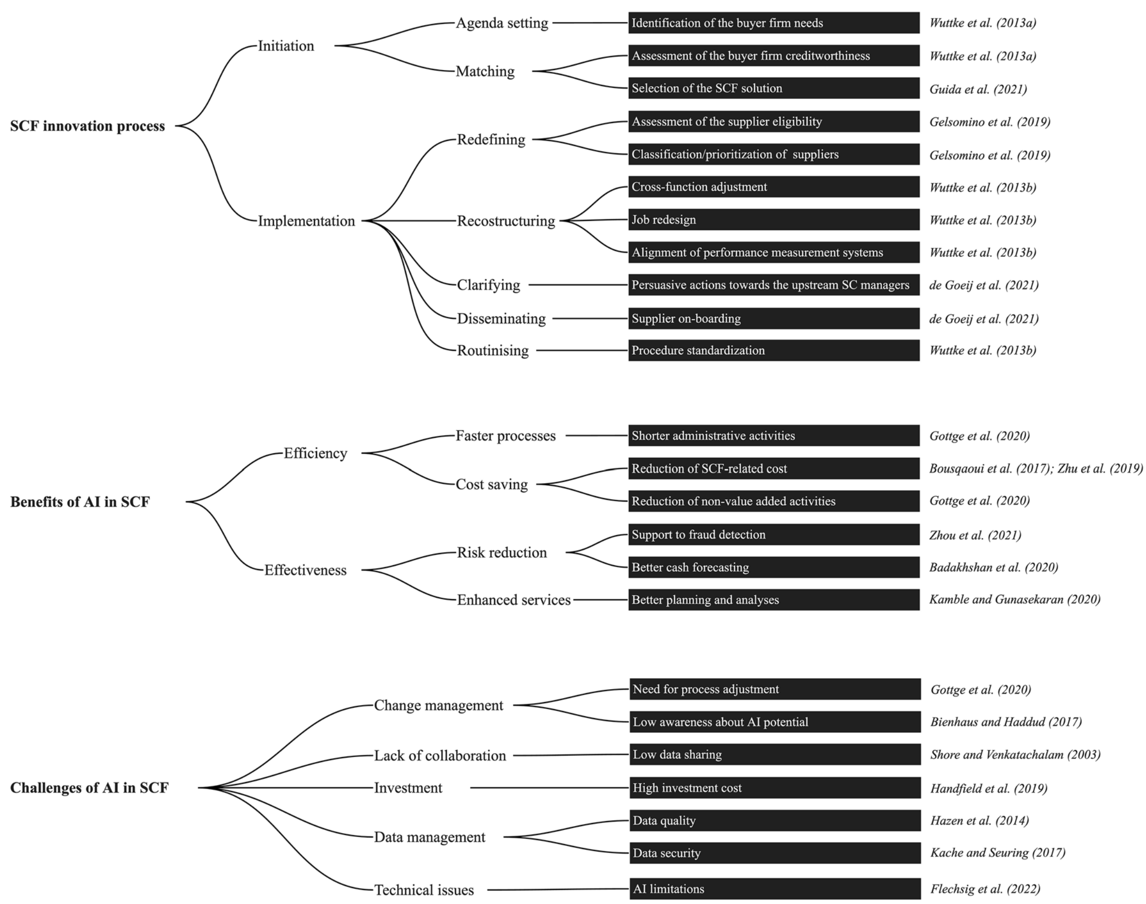

Fig. 4 Coding tree

Annex C

Table 9 Cross-case table: SCF Innovation process

	Initiation		**Implementation**				
	Agenda Setting	Matching	Redefining	Restructuring	Clarifying	Disseminating	Routinising
Company A	N/D	N/D	Supplier's categorisation	N/D	N/D	Suppliers onboarding	Early payments assessment Administrative procedures automation
Company B	N/D	N/D	Supplier's categorisation Supplier's credit rating	N/D	N/D	N/D	Detect risky internal employees Administrative procedures automation

	Initiation		Implementation				
	Agenda Setting	Matching	Redefining	Restructuring	Clarifying	Disseminating	Routinising
Company C	Commercial activities	Solution proposal Buyer's credit rating Buyer's fraud detection	Supplier's categorisation	N/D	N/D	N/D	N/D
Company D	N/D	N/D	N/D	N/D	N/D	Suppliers onboarding	Administrative procedures automation
Company E	Commercial activities	Buyer's credit rating Buyer's fraud detection	Supplier's credit rating Supplier's fraud detection	N/D	N/D	Suppliers onboarding	Administrative procedures automation Monitoring and improvement
Company F	N/D	Buyer's credit rating Buyer's fraud detection Buyer's credit limit	N/D	N/D	N/D	N/D	N/D
Company G	N/D	Solution proposal	Supplier's fraud detection Supplier's categorisation Supplier's credit rating	N/D	N/D	N/D	Administrative procedures automation Monitoring and improvement Fraud detection
Company H	N/D	Buyer's credit rating Buyer's credit limit	Supplier's credit rating Supplier's credit limit	N/D	N/D	N/D	N/D
Company I	N/D	Buyer's credit rating	Supplier's credit rating	N/D	N/D	N/D	Early payments assessment Monitoring and improvement
Company J	N/D	N/D	Supplier's credit rating Supplier's categorisation	N/D	N/D	N/D	Administrative procedures automation

Table 10 Cross-case table: Benefits

	Benefits		
	Buyer	**Suppliers**	**SCF Provider**
Company A	- Improved personalisation and user-friendliness	- Improved personalisation and user-friendliness	- Better front office response
Company B	- Internal fraud detection - Faster administrative procedures	- Internal fraud detection - Faster administrative procedures	N/D
Company C	- Faster application assessment - Increased objectivity of credit evaluation - Better understanding customer's needs	N/D	- Increased objectivity of credit evaluation - Internal fraud detection

	Benefits		
	Buyer	Suppliers	SCF Provider
Company D	- Faster administrative procedures - Opportunity to onboard higher number of suppliers - Non-value-added activities saving	- Faster administrative procedures - Opportunity to onboard higher number of suppliers - Non-value-added activities saving	N/D
Company E	- Faster financing - Faster administrative procedures	- Faster financing - Faster administrative procedures	- Internal fraud detection
Company F	- Faster application assessment - Increased objectivity of credit evaluation	N/D	- Faster application assessment - Internal fraud detection - Increased objectivity of credit evaluation
Company G	- Non-value-added activities savings - Faster administrative procedures	- Non-value-added activities savings - Faster administrative procedures	- Better understanding of customer's needs
Company H	- Increased objectivity of credit evaluation	N/D	- Non-value-added activities savings - Increased objectivity of credit evaluation
Company I	- Improvement of cash forecasting	- Improvement of cash forecasting	N/D
Company J	- Non-value-added activities savings - Faster administrative procedures - Faster supplier onboarding	- Lower financing cost - Non-value-added activities savings - Faster administrative procedures - Faster supplier onboarding	- Better understanding of customer's needs

Table 11 Cross-case table: Challenges

	Challenges		
	Buyer	Suppliers	SCF Provider
Company A	N/D	N/D	- AI errors
Company B	- Inadequate technology infrastructure - Process adjustment - Low data sharing	- Inadequate technology infrastructure - Process adjustment - Low data sharing	- Low data sharing - Inadequate technology infrastructure
Company C	N/D	N/D	- Dataset significance - AI errors
Company D	N/D	N/D	- Need for a short ROI
Company E	- Low data sharing	- Low data sharing	- Low data sharing - High investment cost
Company F	N/D	N/D	- Dataset significance
Company G	- Low data sharing	- Low data sharing	- Low data sharing - Data security - Black box problem - Application area identification
Company H	- Inadequate technology infrastructure - Black box problem	- Inadequate technology infrastructure	- Inadequate technology infrastructure - Black box problem

	Challenges		
	Buyer	**Suppliers**	**SCF Provider**
Company I	- Data maintenance	- Data maintenance	- Data significance - Regulatory issue
Company J	- Low data sharing - Black box problem	- Data maintenance - Low data sharing	- Low data sharing

Funding Open access funding provided by Politecnico di Milano within the CRUI-CARE Agreement.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

References

Aksoy A, Öztürk N (2011) Supplier selection and performance evaluation in just-in-time production environments. Expert Syst Appl 38(5):6351–6359

Amankwah-Amoah J, Lu Y (2022) Harnessing AI for business development: a review of drivers and challenges in Africa. Prod Plan Control 1–10

Arunachalam D, Kumar N, Kawalek JP (2018) Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. Transp Res Part E: Logist Transp Rev 114:416–436

Badakhshan E, Humphreys P, Maguire L, McIvor R (2020) Using simulation-based system dynamics and genetic algorithms to reduce the cash flow bullwhip in the supply chain. Int J Prod Res 58(17):5253–5279

Bals C (2019) Toward a supply chain finance (SCF) ecosystem–Proposing a framework and agenda for future research. J Purch Supply Manag 25(2):105–117

Banerjee A, Lücker F, Ries JM (2021) An empirical analysis of suppliers' trade-off behaviour in adopting digital supply chain financing solutions. Int J Oper Prod Manag 41(4):313–335

Baryannis G, Validi S, Dani S, Antoniou G (2019) Supply chain risk management and artificial intelligence: state of the art and future research directions. Int J Prod Res 57(7):2179–2202

Biju AK, Thomas AS, Thasneem J (2024) Examining the research taxonomy of artificial intelligence, deep learning & machine learning in the financial sphere—a bibliometric analysis. Qual Quant 58(1):849–878

Bienhaus F, Haddud A (2018) Procurement 4.0: factors influencing the digitisation of procurement and supply chains. Bus Process Manag J 24(4):965–984

Bonzani A, Moretto A, Caniato F (2018) Costs and benefits of Supply Chain Finance solutions: is it always worth it? The supply chain finance essential knowledge series. Supply Chain Finance Community, pp 1–32

Bousqaoui H, Achchab S, Tikito K (2017) Machine learning applications in supply chains: An emphasis on neural network applications. 2017 3rd International Conference of Cloud Computing Technologies and Applications. CloudTech. IEEE, USA, pp 1–7

Brintrup A, Kosasih E, Schaffer P, Zheng G, Demirel G, MacCarthy BL (2024) Digital supply chain surveillance using artificial intelligence: definitions, opportunities and risks. Int J Prod Res 62(13):4674–4695. https://doi.org/10.1080/00207543.2023.2270719

Caniato F, Gelsomino LM, Perego A, Ronchi S (2016) Does finance solve the supply chain financing problem? Supply Chain Manag Int J 21(5):534–549

Caniato F, Henke M, Zsidisin GA (2019) Supply chain finance: historical foundations, current research, future developments. J Purch Supply Manag 25(2):99–104

Chen DQ, Preston DS, Swink M (2015) How the use of big data analytics affects value creation in supply chain management. J Manag Inf Syst 32(4):4–39. https://doi.org/10.1080/07421222.2015.1138364. issn: 0742-1222, 1557-928X

Chen J, See KC (2020) Artificial intelligence for COVID-19: rapid review. J Med Internet Res 22(10):e21476

Chen L, Moretto A, Jia F, Caniato F, Xiong Y (2021) The role of digital transformation to empower supply chain finance: current research status and future research directions (Guest editorial). Int J Oper Prod Manag 41(4):277–288

Chen S, Du J, He W, Siponen M (2022) Supply chain finance platform evaluation based on acceptability analysis. Int J Prod Econ 243:108350

Chen X, Hu C (2011) The value of supply chain finance. Supply chain management-applications and simulations. pp 111–132

Chehbi-Gamoura S, Derrouiche R, Damand D, Barth M (2020) Insights from big data analytics in supply chain management: an all-inclusive literature review using the SCOR model. Prod Plann Control 31(5):355–382. https://doi.org/10.1080/09537287.2019.1639839

Choi TY, Hofmann E, Templar S, Rogers DS, Leuschner R, Korde RY (2023) The supply chain financing ecosystem: Early responses during the COVID-19 crisis. J Purch Supply Manag 29(4):100836

Crafts N (2021) Artificial intelligence as a general-purpose technology: an historical perspective. Oxf Rev Econ Pol 37(3):521–536. https://doi.org/10.1093/oxrep/grab012

De Boer R, van Bergen M, Steeman M (2015) Supply chain finance, its practical relevance and strategic value.

De Bruyn A, Viswanathan V, Beh YS, Brock JK, Von Wangenheim F (2020) Artificial intelligence and marketing: Pitfalls and opportunities. J Interact Mark 51(1):91–105

de Campos Martins F, Simon AT (2018) Supply chain 4.0 challenges. 2nd International Symposium on Supply Chain 4.0, p 50

de Goeij C, Gelsomino LM, Caniato F, Moretto A, Steeman M (2021) Understanding SME suppliers' response to supply chain finance: a transaction cost economics perspective. Int J Phys Distrib Logist Manag 51(8):813–836

Eisenhardt KM (1989) Building theories from case study research. Acad Manag Rev 14(4):532–550
Eisenhardt KM, Bourgeois LJ III (1988) Politics of strategic decision making in high-velocity environments: Toward a midrange theory. Acad Manag J 31(4):737–770
Flechsig C, Anslinger F, Lasch R (2022) Robotic Process Automation in purchasing and supply management: A multiple case study on potentials, barriers, and implementation. J Purch Supply Manag 28(1):100718
Fu Y, Zhu J (2016) Network supplier credit evaluation model based on big data. J Cent Univ Fin Econ 348:74–83
Gelsomino LM, de Boer R, Steeman M, Perego A (2019) An optimisation strategy for concurrent Supply Chain Finance schemes. J Purch Supply Manag 25(2):185–196
Gelsomino LUCA, Mangiaracina R, Perego A, Tumino A (2016) Supply chain finance: modelling a dynamic discounting programme. J Adv Manag Sci 4(4):283–291
Giannakis M, Louis M (2011) A multi-agent based framework for supply chain risk management. J Purch Supply Manag 17(1):23–31
Gibbert M, Ruigrok W, Wicki B (2008) What passes as a rigorous case study? Strateg Manag J 29(13):1465–1474
Gomm ML (2010) Supply chain finance: applying finance theory to supply chain management to enhance finance in supply chains. Int J Logistics Res Appl 13(2):133–142. https://doi.org/10.1080/13675560903555167
Gottge S, Menzel T, Forslund H (2020) Industry 4.0 technologies in the purchasing process. Ind Manag Data Syst 120(4):730–748
Guida M, Caniato F, Moretto A, Ronchi S (2023) The role of artificial intelligence in the procurement process: State of the art and research agenda. J Purch Supply Manag 29(2):100823
Guida M, Moretto AM, Caniato FFA (2021) How to select a supply chain finance solution? J Purch Supply Manag 27(4):100701
Gunasekaran A, Ngai EW (2004) Information systems in supply chain integration and management. Eur J Oper Res 159(2):269–295
Hazen BT, Boone CA, Ezell JD, Jones-Farmer LA (2014) Data quality for data science, predictive analytics, and big data in supply chain management: an introduction to the problem and suggestions for research and applications. Int J Prod Econ 154:72–80
Handfield R, Jeong S, Choi T (2019) Emerging procurement technology: data analytics and cognitive analytics. Int J Phys Distrib Logist Manag 49(10):972–1002. https://doi.org/10.1108/IJPDLM-11-2017-0348
Hung JL, He W, Shen J (2020) Big data analytics for supply chain relationship in banking. Ind Mark Manag 86:144–153
IEEE Corporate Advisory Group (2017) IEEE guide for terms and concepts in intelligent process automation. IEEE, New York City
Ivanov D (2021) Digital supply chain management and technology to enhance resilience by building and using end-to-end visibility during the COVID-19 pandemic. IEEE Trans Eng Manag
Jia F, Blome C, Sun H, Yang Y, Zhi B (2020a) Towards an integrated conceptual framework of supply chain finance: An information processing perspective. Int J Prod Econ 219:18–30
Jia F, Zhang T, Chen L (2020b) Sustainable supply chain finance: towards a research agenda. J Clean Prod 243:118680
Kache F, Seuring S (2017) Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. Int J Oper Prod Manag 37(1):10–36
Kamble SS, Gunasekaran A (2020) Big data-driven supply chain performance measurement system: a review and framework for implementation. Int J Prod Res 58(1):65–86. https://doi.org/10.1080/00207543.2019.1630770
Karttunen E, Lintukangas K, Hallikas J (2023) Digital transformation of the purchasing and supply management process. Int J Phys Distrib Logist Manag 53(5/6):685–706
Khashman A (2011) Credit risk evaluation using neural networks: Emotional versus conventional models. Appl Soft Comput 11(8):5477–5484
Klapper L (2006) The role of factoring for financing small and medium enterprises. J Bank Fin 30(11):3111–3130
Kumar Dadsena K, Pant P (2023) Analyzing the barriers in supply chain digitization: sustainable development goals perspective. Oper Manag Res 16(4):1684–1697
Lamoureux JF, Evans TA (2011) Supply chain finance: a new means to support the competitiveness and resilience of global value chains. Available at SSRN 2179944.
Li R (2018) E-commerce supply chain internet financing research. Rural Financ Res 1(006):30–34
Li Y, Jiang W, Yang L, Wu T (2018) On neural networks and learning systems for business computing. Neurocomputing 275:1150–1159
Liddy ED (2001) Natural language processing
Liebl J, Hartmann E, Feisel E (2016) Reverse factoring in the supply chain: objectives, antecedents and implementation barriers. Int J Phys Distrib Logist Manage 46(4)
Lorentz H, Aminoff A, Kaipia R, Pihlajamaa M, Ehtamo J, Tanskanen K (2020) Acquisition of supply market intelligence – an information processing perspective. J Purch Supply Manag. https://doi.org/10.1016/j.pursup.2020.100649
Lu J, Wu D, Mao M, Wang W, Zhang G (2015) Recommender system application developments: a survey. Decis Support Syst 74:12–32. https://doi.org/10.1016/j.dss.2015.03.008
Mantere S, Ketokivi M (2013) Reasoning in organization science. AMR 38(1):70–89
McKinsey (2015) Supply-chain finance: The emergence of a new competitive landscape. McKinsey on Payments 8(22):10–16
Min H (2010) Artificial intelligence in supply chain management: theory and applications. Int J Log Res Appl 13(1):13–39
Mogaji E, Nguyen NP (2022) Managers' understanding of artificial intelligence in relation to marketing financial services: insights from a cross-country study. Int J Bank Mark 40(6):1272–1298
More D, Basu P (2013) Challenges of supply chain finance: A detailed study and a hierarchical model based on the experiences of an Indian firm. Bus Process Manag J 19(4):624–647
Moretto A, Caniato F (2021) Can Supply Chain Finance help mitigate the financial disruption brought by Covid-19? J Purch Supply Manag 27(4):100713
Moretto A, Grassi L, Caniato F, Giorgino M, Ronchi S (2019) Supply chain finance: From traditional to supply chain credit rating. J Purch Supply Manag 25(2):197–217
Nguyen T, Li ZHOU, Spiegler V, Ieromonachou P, Lin Y (2018) Big data analytics in supply chain management: a state-of-the-art literature review. Comput Operat Res 98:254–264. https://doi.org/10.1016/j.cor.2017.07.004
O'Connor C, Joffe H (2020) Intercoder reliability in qualitative research: debates and practical guidelines. Int J Qual Methods 19:1–13
Olan F, Liu S, Suklan J, Jayawickrama U, Arakpogun EO (2022) The role of Artificial Intelligence networks in sustainable supply chain finance for food and drink industry. Int J Prod Res 60(14):4418–4433
Osservatorio Supply Chain Finance (2020) Supply Chain Finance: level up!
Pfohl HC, Gomm M (2009) Supply chain finance: optimizing financial flows in supply chains. Logist Res 1:149–161. https://doi.org/10.1007/s12159-009-0020-y
Priore P, Ponte B, Rosillo R, de la Fuente D (2019) Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. Int J Prod Res 57(11):3663–3677

Rana J, Daultani Y (2023) Mapping the role and impact of artificial intelligence and machine learning applications in supply chain digital transformation: A bibliometric analysis. Oper Manag Res 16(4):1641–1666

Rogers EM (2003) Diffusion of innovations. Free Press, New York

Ronchini A, Moretto A, Caniato F (2021) A decision framework for inventory-and equipment-based supply chain finance solutions. J Purch Supply Manag 27(4):100712

Saberi S, Kouhizadeh M, Sarkis J (2019) Blockchains and the supply chain: Findings from a broad study of practitioners. IEEE Eng Manag Rev 47(3):95–103

Schreier M (2018) Sampling and generalization. In: The SAGE handbook of qualitative data collection. SAGE Publications

Schoenherr T, Speier-Pero C (2015) Data science, predictive analytics, and big data in supply chain management: Current state and future potential. J Bus Logist 36(1):120–132

Shawar BA, Atwell E (2007) Chatbots: are they really useful? J Lang Technol Comput Linguist 22(1):29–49

Shore B, Venkatachalam AR (2003) Evaluating the information sharing capabilities of supply chain partners: a fuzzy logic model. Int J Phys Distrib Logist Manag 33(9):804–824. https://doi.org/10.1108/09600030310503343

Seifert D (2010) Collaborative Working Capital Management in Supply Networks. Retrieved August 2013, 31, from École Polytechnique Fédérale De Lausanne: http://biblion.epfl.ch/EPFL/theses/2010/4617/4617_abs.pdf

Singh N, Lai KH, Vejvar M, Cheng TC (2019) Big data technology: challenges, prospects, and realities. IEEE Eng Manag Rev 47(1):58–66

Singh NP, Singh S (2019) Buianalytics into supply chain finance: Thelding supply chain risk resilience: role of big data analytics in supply chain disruption mitigation. Benchmarking 26(7):2318–2342

Song H, Li M, Yu K (2021) Big data analytics in digital platforms: how do financial service providers customise supply chain finance? Int J Oper Prod Man 41(4):410–435

Syed M, Nelson SC (2015) Guidelines for establishing reliability when coding narrative data. Emerg Adulthood 3(6):375–387

Toorajipour R, Sohrabpour V, Nazarpour A, Oghazi P, Fischl M (2021) Artificial intelligence in supply chain management: A systematic literature review. J Bus Res 122:502–517

Trawnih A, Al-Masaeed S, Alsoud M, Alkufahy A (2022) Understanding artificial intelligence experience: A customer perspective. Int J Data Netw Sci 6(4):1471–1484

United Nations - Economic Commission for Europe United Nations Centre for Trade Facilitation and Electronic Business (UN/CEFACT) (2018) Business requirements specification (BRS) - Purchase order financing

Van der Vliet K, Reindorp MJ, Fransoo JC (2015) The price of reverse factoring: Financing rates vs. payment delays. Eur J Oper Res 242(3):842–853

van Hoek R, Larsen JG, Lacity M (2022) Robotic process automation in Maersk procurement–applicability of action principles and research opportunities. Int J Phys Distrib Logist Manag 52(3):285–298

Verma S, Sharma R, Deb S, Maitra D (2021) Artificial intelligence in marketing: Systematic review and future research direction. Int J Inf Manag Data Insights 1(1):100002

Voss C, Tsikriktsis N, Frohlich M (2002) Case research in operations management. Int J Oper Prod Manag 22(2):195–219

Wandfluh M, Hofmann E, Schoensleben P (2016) Financing buyer–supplier dyads: an empirical analysis on financial collaboration in the supply chain. Int J Log Res Appl 19(3):200–217

Wang L, Yan J, Chen X, Xu Q (2021) Do network capabilities improve corporate financial performance? Evidence from financial supply chains. Int J Oper Prod Manag 41(4):336–358

Wu WY, Sukoco BM, Li CY, Chen SH (2009) An integrated multi-objective decision-making process for supplier selection with bundling problem. Expert Syst Appl 36(2):2327–2337

Wuttke DA, Blome C, Henke M (2013a) Focusing the financial flow of supply chains: An empirical investigation of financial supply chain management. Int J Prod Econ 145(2):773–789

Wuttke DA, Blome C, Foerstl K, Henke M (2013b) Managing the innovation adoption of supply chain finance - Empirical evidence from six European case studies. J Bus Logist 34(2):148–166

Yarramalli SS, Manasa Ponnam RS, Koteswara Rao GR, Fathimabi SK Madasu PD (2020) Digital procurement on systems applications and products (SAP) cloud solutions. 2nd International Conference on Inventive Research in Computing Applications

Yin RK (2018) Case study research and applications, Vol. 6. Sage, Thousand Oaks, CA

Yoo SH, Choi TY, Kim D (2021) Integrating sourcing and financing strategies in multi-tier supply chain management. Int J Prod Econ 234:108039

Yu W, Wong CY, Chavez R, Jacobs MA (2021) Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. Int J Prod Econ 236:108135. https://doi.org/10.1016/j.ijpe.2021.108135. https://www.sciencedirect.com/science/article/pii/S0925527321001110. ISSN 0925-5273

Zaks I, Lapouchnian A (2018) Supply Chain Finance and Artificial Intelligence-a game changing relationship? Receivables Finance Technology 32–37

Zhang M, Huang Q, Zhao X, Ma L (2021) The impact of information integration on purchase order finance and new product launch: a case study. Int J Oper Prod Manag 41(4):359–382

Zhou H, Sun G, Fu S, Fan X, Jiang W, Hu S, Li L (2020) A distributed approach of big data mining for financial fraud detection in a supply chain. Comput Mater Con 64(2):1091–1105

Zhu Y, Xie C, Sun BW, Yan XG (2016) Predicting China's SME credit risk in supply chain financing by logistic regression, artificial neural network and hybrid models. Sustainability 8(5):433

Zhu Y, Xie C, Wang GJ, Yan XG (2017) Comparison of individual, ensemble and integrated ensemble machine learning methods to predict China's SME credit risk in supply chain finance. Neural Comput Appl 28(1):41–50

Zhu Y, Zhou L, Xie C, Wang GJ, Nguyen TV (2019) Forecasting SMEs' credit risk in supply chain finance with an enhanced hybrid ensemble machine learning approach. Int J Prod Econ 211:22–33