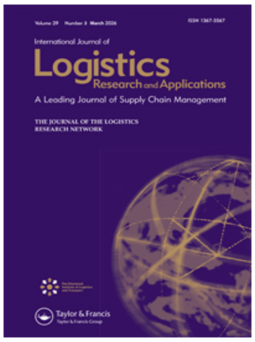

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Perceptions of AI adoption and their impact on supply chain learning

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ABSTRACT

Operationalisation of supply chain learning (SCL) is a major challenge. Technologies such as artificial intelligence (AI) are expected to favour supply chain information sharing, collaboration, and coordination, hence, supporting SCL. This paper examines how organisations' perceptions about AI adoption influence SCL, exploring the relationship between AI's perceived usefulness and ease of use with the SCL dimensions. We performed an online survey-based investigation with 206 Brazilian practitioners from different organisations of several industry sectors, whose responses were examined using multivariate data techniques. Similar trends in results were observed regardless of whether the relationship was between the focal company and its suppliers or between the focal company and its customers. When the perception about AI's usefulness and ease of use are both low, captive SCL tends to occur; when both are high, SCL might occur in a distributed way. A consortium SCL prevails if only AI's perceived ease of use is high; a selective SCL occurs if only the perceived usefulness is high. Identifying how SCL is impacted by organisations' perceptions about AI adoption may help managers to prioritise their digitalisation efforts, adjusting them according to the expected type of knowledge to be created and shared across the supply chain.

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Supply chain management; supply chain learning; artificial intelligence; Industry 4.0

1. Introduction

An organisation's ability to accumulate knowledge about customers, suppliers, and other major participants in its supply chains (SCs) has emerged as an important theme in operations management (Willis, Genchev, and Chen 2016), being considered a strategic action among SC partners (Yang 2016). To that effect, supply chain learning (SCL), derived from organisational learning, is the collective learning that occurs among multiple SC players (Silvestre et al. 2020, 2023; Sun et al. 2024). Nevertheless, SCL is considered a major challenge which has become more apparent because of the disruptive events of the COVID-19 pandemic (Kumar et al. 2021). This challenge

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is also aggravated by the poor understanding of an evolving SCL concept (Yang, Jia, and Xu 2019), and the scant literature directly focusing on how learning happens in a SC context (Silvestre et al. 2023). Due to its complex nature, SCL may also be undermined by conflicting interests of multiple SC partners, resulting in trade-offs that can negatively affect performance (Blome, Schoenherr, and Eckstein 2014; Villena, Choi, and Revilla 2021). In this sense, SC players have put much effort to improve information sharing, collaboration, and coordination to mitigate these learning issues (Cheung, Myers, and Mentzer 2010; Huo, Haq, and Gu 2021). This process must be aligned with an adequate SC integration strategy, both internally and externally (with suppliers and customers), in which work should be done on three main areas that affect SCL, information integration, coordination and resource sharing and organisational relationship linkages (Alfalla-Luque, Medina-Lopez, and Dey 2013; Lee 2000).

With the technological advances boosted by the Fourth Industrial Revolution (a.k.a. Industry 4.0 – I4.0), new digital solutions have been developed, enabling the enhancement of information transparency, communication, trust, and collaboration among SC players (Fatorachian and Kazemi 2021; Koh, Orzes, and Jia 2019; Tortorella et al. 2022). The integration of I4.0 digital technologies, such as artificial intelligence (AI), into SCs' operations is likely to increase their ability to demand forecasting, problem-solving, production capacity, product/service development, and optimisation of inventory levels, routing, and scheduling (Jackson et al. 2024; Sharma et al. 2022a; Toorajipour et al. 2021). In terms of financial benefits, McKinsey & Company (2022) estimated that in the next twenty years SCs will derive between US$1.3trn and US$2trn a year in economic value from using AI. Such benefits have been rising the interest on AI utilisation among SC players, from which 80% plan to have AI adopted (at any given level) by 2026 (Gartner 2023).

Despite these positive indications, literature evidence is scarce or scattered when it specifically comes to the role of AI for SCL (Modgil, Singh, and Hannibal 2022; Pournader et al. 2021; Rolf et al. 2023), addressing this relationship only tangentially or superficially. Therefore, not only is SCL still a poorly understood phenomenon but also the body of knowledge on the effect of how AI is perceived by organisations on it is incipient, highlighting an important theoretical gap that raises the following research question (RQ):

RQ. How does an organization's AI perception impact SCL?

To answer this RQ, this study aims at investigating the relationship between AI's perceptions and SCL using online survey-based research. Empirical evidence collected from 206 top and middle managers from different industry sectors in Brazil was assessed utilising multivariate data analysis techniques. According to AI Asia Pacific Institute (2025), Brazil has recently emerged as one of the leading centres of AI innovation in Latin America, fostering AI development in many industry sectors and establishing a high-potential ecosystem for AI research and practical applications. For instance, investments in AI and generative projects in Brazil should exceed USD 2.4 billion by 2025 (Schaal and Diniz 2025). Additionally, most SCs in Brazil are experiencing significant growth (Horizon Grand View Research 2025), despite the existing challenges (e.g. port bottlenecks and infrastructure limitations) that undermine efficient operations and increase costs (Freitas and Partyka 2022). These characteristics create the proper settings for developing our research, justifying the context of this study.

Following Silvestre et al.'s (2023) typology, the impacts of AI's perceptions were studied in terms of two main SCL dimensions: SCL driver and SCL network. This work was framed within the concepts from Technology Acceptance Model (TAM) (Davis 1989; Davis, Bagozzi, and Warshaw 1989), which claim that when users are introduced to a new technology (e.g. AI), various factors affect their decisions about how and when they will use it, particularly: (*i*) perceived usefulness (PU) and perceived ease-of-use (PEOU). Despite existing criticism, TAM is one of the most influential theoretical models being utilised to assess the acceptance level of new technologies in different work settings (Fernando et al. 2023; King and He 2006; Legris, Ingham, and Collerette 2003; Lin, Yang, and Chang 2025; Oulmakki et al. 2024), which justified our choice. Additionally, we used the connectivism learning theory (Downes 2010; Siemens 2005), developed with the digital transformation era, to pose the discussion of our results. Connectivism is a relatively new learning theory that suggests that individuals remain gaining knowledge after formal education through technology-based means, such as networking, experience, and information access (Duke, Harper, and Johnston 2013). Learning is conceptualised as a process of connecting information sources or specialised nodes, where the development of the capacity to know accurate up-to-date knowledge is critical (Siemens 2005). Since AI is part of the technological portfolio of I4.0, discussing our findings from connectivism theory's perspective becomes reasonable.

The contribution of this work is two-fold. First, in theoretical terms, as AI is a relatively recent phenomenon, its implications are still under investigation. Hence, using concepts from TAM and connectivism learning theory, we verified how different combinations of AI PU and PEOU might be associated with SCL dimensions. This enlightens how perceptions about AI may promote different types of SCL. Second, this study offers practical implications to SC players and stakeholders. Firstly, the identification of how SCL is affected by AI's perceptions may help SC managers to prioritise their digitalisation efforts, adjusting them according to the expected type of knowledge to be created and shared. Secondly, since SCL driver and network may shift as AI is differently perceived in multiple SC tiers, managers may design learning strategies to benefit from it, potentially entailing positive effects on operational performance and gaining competitive advantages based on more assertive decision-making and effective problem-solving.

The remainder of this paper is structured as follows. Section 2 presents the background on the main concepts utilised in this work. Section 3 describes the methodology, whose results are presented and discussed in section 4. Section 5 concludes the paper by discussing the theoretical and practical implications of our research, highlighting its limitations.

2. Background

2.1. Supply chain learning

Inter-organisational learning is generally observed between two organisations, whereas SCL is focused on SCs and goes beyond a dyadic relationship (e.g. only one buyer and one supplier), engaging both upstream and downstream organisations (Flint, Larsson, and Gammelgaard 2008; Jia and Lamming 2013). In fact, Yang, Jia, and Xu (2019) suggested that SCL may occur either throughout the SC or among at least three SC tiers, i.e. focal company, a supplier, and a customer. However, in practical terms, SCL often happens solely between focal companies and first tier suppliers without the involvement of other tiers, since focal companies tend to have less control on them (Bessant, Kaplinsky, and Lamming 2003; Gong et al. 2018; Jia, Gong, and Brown 2019). Additionally, SCL may be impacted by different dimensions, such as knowledge type (Schoenherr, Griffith, and Chandra 2014), source (Cassiman and Veugelers 2006) and content (Zhu, Krikke, and Caniels 2018), and learning process (Malerba 1992).

Bessant, Kaplinsky, and Lamming (2003) suggested the categorisation of SCL into three phases: (*i*) set up, which establishes the set of procedures to enable SCL, (*ii*) operating, which translates those procedures into routines and norms that guide behaviours between and within SC players, and (*iii*) sustaining, which manages the needs (e.g. metrics and benchmarking) for continuous learning. In practical terms, SCL may be denoted by three main processes: (*i*) knowledge generation, which encompasses the co-recognition of innovation variables that may affect the performance of current and future operations, (*ii*) knowledge transfer, which refers to the process by which applicable innovation information and know-how are transferred among SC players, and (*iii*) knowledge application, which corresponds to the institutionalisation of new product/market information and know-how by shifting management behaviours and approaches to improve performance (Esper et al. 2010; Zhu, Krikke, and Caniels 2018).

Although still scarce, Silvestre et al. (2023) analysed the existing literature on SCL to develop a typology based on two main dimensions: SCL driver and SCL network. SCL driver represents the driving force behind the creation and diffusion of knowledge across the SC. It can be led by an influential focal company or one or more non-focal companies (Bessant, Kaplinsky, and Lamming 2003; Gong et al. 2018), with learning trade-offs in both situations. SCL network indicates the extent to which new knowledge is generated by and/or shared with players operating in either one or multiple SCs (Sauer, Silva, and Schleper 2022; Silvestre 2015), hence, being categorised as closed or open according to such an extent. The combination of both dimensions yields four types of SCL (Silvestre et al. 2023):

(i) Captive SCL: occurs when learning efforts are driven by the focal company through a closed network representing the interests of the most influential company in the SC (Huo, Flynn, and Zhao 2017), and creating and sharing knowledge only within the respective SC. The coordination of SCL efforts is usually facilitated and properly aligned, although it may be less legitim and embedded in myopic views;
(ii) Consortium SCL: refers to learning efforts driven by non-focal companies through a closed network. It represents the interests of groups of players or stakeholders, hence, being more legitim (Macdonald 2007), although knowledge is still retained within the same SC;
(iii) Selective SCL: happens when learning efforts are driven by focal companies through an open network. The focal company selectively chooses players within and outside its SC to generate and share knowledge (Yao, Dong, and Dresner 2012), thus increasing its synergy and impact (Niu and Shen 2022); and
(iv) Distributed SCL: corresponds to learning efforts driven by non-focal companies through an open network. These efforts involve a diverse set of players (i.e. high legitimacy) and generate knowledge that permeates multiple SCs (i.e. broader views) (Sawhney and Prandelli 2000). Nevertheless, their coordination and alignment among players tend to be more complex.

A SC that learns through the utilisation of these four types of SCL to support the achievement of its objectives may be denoted as a 'Learning SC' (Silvestre et al. 2023). Overall, SCL can be considered a strategic requirement for building and maintaining competitiveness, supporting the achievement of superior performance results (Bessant, Kaplinsky, and Lamming 2003). SCL is also likely to promote a platform for good practices exchange among SC players, facilitating the development of skill sets and enabling the establishment of effective learning networks (Huo, Haq, and Gu 2021). The adoption of new technologies, such as AI, might boost SCL and lean it to other directions beyond the traditionally expected boundaries. Nevertheless, research on the relationship between AI and SCL is still incipient, raising doubts about its potential and characterising a gap in the existing body of knowledge.

2.2. Artificial intelligence and supply chain management

AI is a technology that allows computers and digital devices to learn, read, write, talk, see, create, play, analyse, make recommendations, and do other things humans do (Benbya, Davenport, and Pachidi 2020). AI, which was deemed as an academic discipline in 1956 (Russell and Norvig 2021), combines computer science and robust datasets to enable problem-solving, make predictions or classifications based on input data. The recent availability of advanced algorithms together with large datasets and greater computational capacity has increased AI's popularity and pervasiveness across different industry sectors (Cao et al. 2021). This leads to a number of AI applications, such as recommendation systems, human-speech interacting devices, advanced web search engines, self-driving cars, and generative and creative tools (Modgil, Singh, and Hannibal 2022; Pournader et al. 2021; Rolf et al. 2023).

In technological terms, AI characteristics allow the building of new types of functionality for information systems that support operations and SCs (Helo and Hao 2022). For instance, AI might be adopted in the following areas:

(a) Learning systems that can adapt behaviours based on real-time data (Kabudi, Pappas, and Olsen 2021);
(b) Situation-aware systems that are able to identify the existing conditions, and adapt behaviours accordingly (D'Aniello et al. 2022);
(c) Autonomous decision-making systems that can make decisions differently from traditional decision support systems (Sharma et al. 2022b); and
(d) Processing of streaming images, video, audio and non-structured text type of data (Jayanthiladevi et al. 2020).

Despite the diversity of AI applications, most of them still adopt deep learning and natural language processing to carry out tasks, and rapidly and logically assess large datasets towards patterns identification (Von Krogh 2018; Zhang and Lu 2021). Additionally, existing issues still prevent organisations from a more extensive use of AI (Mikalef et al. 2021), such as lack of transparency, concerns about data privacy and security, disbelief in human-machine relations, and biases when devising or training algorithms (Chiu, Zhu, and Corbett 2021; Levy 2018; Leyer and Schneider 2021). In a multi-tier SC context, these issues may undermine collaboration and trust among different players, leading to contradictory effects on SCL (Pfaff, Birkel, and Hartmann 2023). The need for better understanding such effects of AI on SCL has motivated our research.

In the I4.0 context, AI has emerged as a key enabler for management approaches, potentially reshaping the landscape of SC operations. Pournader et al. (2021) indicated that organisations adopt AI for many SC operations, particularly searching for better decision-making processes. Soleimani (2018) expand this discussion by suggesting four SC attributes as potential applications of AI; they are: (*i*) optimisation, (*ii*) prediction, (*iii*) modelling and simulation, and (*iv*) decision support. Regardless of the intricacies of the AI application, there is an overall agreement that it can increase visibility and transparency in SCs, improving customer products/services and satisfaction (Helo and Hao 2022). This has motivated big SC players (e.g. Amazon, Walmart and Philips) to heavily invest in AI as a supporting tool for SC management, setting the path for other organisations (Dwivedi et al. 2021; Mahroof 2019).

However, the use of AI has been predominantly reported in isolated applications or proofs of concept, with little understanding about how it could conduct to capability building at the SC level (Fountaine, McCarthy, and Saleh 2019; Sharma et al. 2022a). In the same vein, Cannas et al. (2023) verified the relationship between AI and SC management according to the SCOR (Supply Chain Operations Reference) processes, suggesting that evidence of AI applications in SCs is more commonly found in the 'make' process. Complementarily, Helo and Hao (2022) proposed that AI applications may address SC problems from two main aspects: (*i*) advanced automatic infrastructure, which corresponds to the fact that AI can leverage and optimise improvement efforts derived from a combination between artificial and human intelligence in addition to fully automated decision-making; and (*ii*) optimised business processes, which indicates that AI optimises businesses by facilitating the monitoring, analysis, and action. Overall, Riahi et al. (2021) emphasise the importance of organisations positioning themselves regarding the desired goals when adopting AI in their SCs, since this will determine the data requirements and select the proper AI tools.

2.3. Technology acceptance model

TAM is an information systems model that describes how users accept and use a technology (desired result), which is affected by behavioural intention (Davis 1989). Behavioural intention relies on people's attitude toward using a technology, which depends on both PU and PEOU (Davis, Bagozzi, and Warshaw 1989). PU refers to the degree to which an individual believes that using a specific technology would be useful to improve his/her work performance. PEOU corresponds to the degree to which an individual thinks that using a specific technology would be effortless (King and He 2006; Legris, Ingham, and Collerette 2003). When both PU and PEOU are high, people are likely to display the required attitude and intention to use the technology. PU and PEOU might be influenced by external variables (e.g. social influence), determining how these perceptions occur (Mogaji et al. 2024), as displayed in Figure 1.

Although TAM has been widely adopted, existing criticisms (e.g. limited explanatory and predictive power, triviality, and lack of any practical value) have motivated its upgrade and continuous development (Ajibade 2018; Malatji, Eck, and Zuva 2020). For instance, Venkatesh and Davis (2000) extended TAM to include social factors (e.g. subjective norm, image, and voluntariness) and cognitive instrumental processes (e.g. job relevance, output quality, and result demonstrability) that influence the behavioural intention to use new technology, leading to TAM2. Then, Venkatesh and Bala (2008) refined it by adding the effects of trust and perceived risk on technology use, resulting in TAM3. Overall, based on extensive literature review, Billanes and Enevoldsen (2021) indicated that TAM, TAM2, and TAM3 have been commonly adopted in studies that approach the use of disruptive digital technologies, which matches our study objective.

Literature evidence specifically using TAM to frame studies approaching AI adoption is also relatively prolific (Balakrishnan et al. 2024; Labrague and Al Harrasi 2025; Xu, Wang, and Lin 2022). For instance, Na et al. (2022) explored the influential factors on end-user's intentions and acceptance of AI-based technology in construction companies using TAM and the technology – organisation – environment (TOE) framework. Subsequently, Na et al. (2023) used TAM to analyse the factors impacting the adoption of AI-driven technologies or products in both South Korea and the UK. Concerning the education context, Li (2023) applied TAM's concepts to explain students' behaviour in terms of the adoption of AI-based systems. Loske and Klumpp (2021) carried out an empirical investigation focused on the use of AI technologies for truck drivers within the retail logistics sector. Overall, there is a large number of studies and great diversity of applications and industry sectors that relied on TAM's concepts to describe AI adoption, which also supports the choice for including such a theoretical lens in our study.

2.4. Connectivism learning theory

Connectivism is a theory that helps understand how learning occurs in the digital transformation era, emphasising the importance of technology and networks in the learning process. It highlights how new digital technologies, such as AI, favour the development of new sources of learning (Duke, Harper, and Johnston 2013; Siemens 2005). Technologies have traditionally allowed individuals to learn and share information among themselves in faster and more effective ways. Connectivism poses that learning does not solely happen within an individual, but also within and across networks

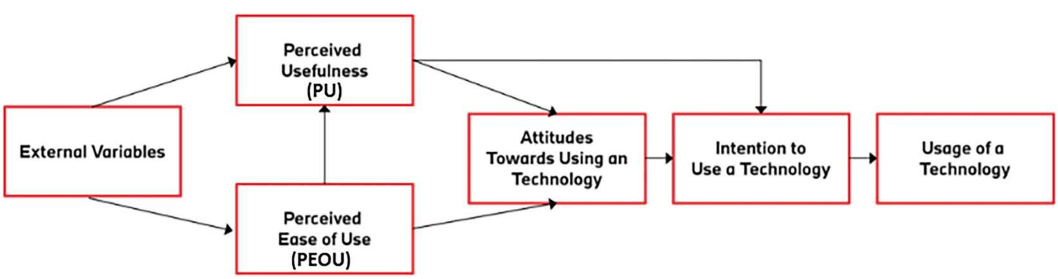

Figure 1. Illustration of TAM (adapted from Davis 1989).

(Kop and Hill 2008). Another unique feature of connectivism is the understanding that learning (conceptualised as actionable knowledge) lies within an organisation or a database, aiming at linking specific information sets. This theory highlights the importance of creating connections and building networks between nodes, which provide for the learner the opportunity to learn more (Siemens 2005). In other words, the connections that enable learning are more relevant than its *status quo* (Kropf 2013).

Connectivism understands knowledge as a network and learning as a process of pattern recognition (Siemens 2006). Viewed as the combination of principles from chaos, network, complexity, and self-organisation theories (Siemens 2005), connectivism's central aspect is the analogy of a network with nodes and connections, in which a node is anything that can be connected to another node (e.g. an organisation, information, data, feelings, and images) (Şahin 2012). Hence, learning occurs as connections are created and network complexity increased. Knowledge resides within networks and it can be stored in different digital formats. Successful networks can be local or global and there are four dynamics (diversity, openness, connectivity and autonomy of the nodes) which increase the probability of the network produce new connective knowledge (Downes 2012). Some additional principles of connectivism comprise (Siemens 2005): (*i*) learning and knowledge rely on diversity of opinions; (*ii*) learning resides in non-human appliances; (*iii*) the perception of connections between fields, ideas and concepts is core; and (*iv*) decision-making is part of learning. Overall, connectivism states that knowledge is distributed across networks where connections and connectedness inform learning (Kop and Hill 2008). Although studies that rely on the connectivism learning theory to investigate AI's implications (e.g. Correia, Água, and Conceição 2024; Liu and Li 2021; Spiess, Salcher, and Dilger 2021) are less frequent, this theory offers useful concepts and assumptions on which our study can build. This helps explaining unexpected findings and generate new insights about the investigated phenomenon.

3. Method

To answer the RQ, we explored the relationship between AI PU and AI PEOU and SCL dimensions by performing an online survey-based investigation with practitioners from Brazilian organisations from several SCs. Quantifying empirical data collected from perceptions of legitimate respondents is a very common methodological approach, allowing higher levels of representativeness and lower costs (Montgomery 2013; Van Selm and Jankowski 2006). The survey data, then, was subject to multivariate data analysis techniques such a cluster analyses and ANOVA to determine how AI PU and AI PEOU affect SCL dimensions. This deductive approach is consistent with previous works of similar exploratory nature (e.g. Marodin et al. 2017; Tortorella, Miorando, and Marodin 2017). The investigated model is represented in Figure 2.

3.1. Questionnaire development and data collection

The questionnaire consisted of four parts (see Appendix A). In the initial part, we gathered information about respondents and their companies. Regarding respondents' information, we asked them about their roles (senior or middle management) and work experience (years) in their companies. With respect to companies' information, we asked about (*i*) company size (number of employees), (*ii*) tier level, and (*iii*) industry sector. As SCL may be affected by the ease of communication and geographical proximity between customers and suppliers (Helmold et al. 2021; Unger 2023), we used the percentage of both suppliers and customers that were onshore as proxy. According to Canuto, Cavallari, and Reis (2013) and verified by Tortorella, Miorando, and Marodin (2017), an index of 70% of onshore suppliers and customers may be used as a reasonable threshold when considering the industry scenario in Brazil. The second part assessed respondents' perceptions (i.e. usefulness and ease-of-use) in relation to AI adoption in the SC. A five-point scale was

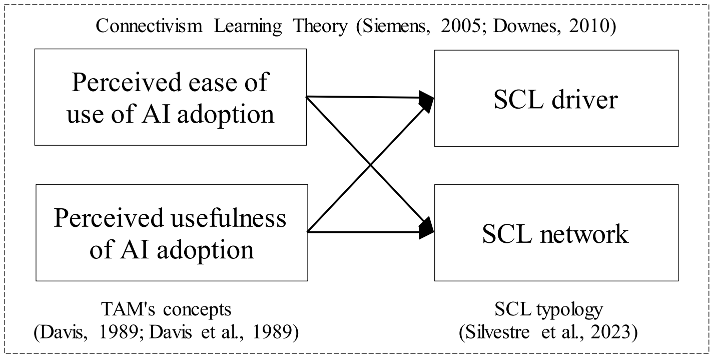

Figure 2. Investigated model.

used, where 1 denoted 'very low' and 5 'very high'. In the third part, we asked respondents about the SCL dimensions exclusively considering the relationship between their company (focal company) and their suppliers. Using a five-point Likert scale, they should indicate whether learning efforts were more frequently (*i*) led by their company or suppliers (non-focal), and (*ii*) shared only with suppliers (closed network) or beyond them (open network). The fourth part assessed similar questions as the third one, except the relationship to be considered was between respondent's company and its customers. Three experts (two academics and one practitioner) assessed the questionnaire regarding its face and content validity, suggesting some minor improvements to increase clarity of some items.

The data collection was conducted using a non-probability sampling method. A non-random selection of firms was carried out based on three pre-determined criteria. First, all participants should work in a company that has been utilising AI with its customers and/or suppliers at a minimum extent. To verify that, the e-mail containing the link of questionnaire had a question asking participants to provide an example of an AI application. We selected respondents based on the depth of their arguments. Second, participants should play a leadership role in their companies; either a middle (coordinator or supervisor) or senior (manager or director) management position. This would contribute to a broader understanding of the investigated phenomenon, assuring the legitimacy of their opinion and minimising short-sighted views. Third, because digital transformation may be subject to some socio-economic characteristics (Tortorella et al. 2021), we solely involved respondents from the same country. As the Brazilian industry has been frequently reported (e.g. Dalenogare et al. 2018; Frank, Dalenogare, and Ayala 2019; Rocha et al. 2023) as a prominent scenario for studies on new digital technologies application, and it represents one of the top ten global economies (Forbes India 2024), it offered an adequate context for conducting our study. It is also worth mentioning that Tortorella et al. (2020) verified the association between new technologies and learning in this industrial context without restricting it to a particular industry sector, corroborating for our socio-economic choice.

Questionnaires were initially sent via e-mail in November 2023–758 potential respondents. Two follow-up e-mails sent in December 2023 and January 2024, respectively, reinforced participation. No specific incentives were provided for participants to respond the questionnaire. The final dataset comprised 206 respondents (see Table 1), yielding a response rate of 27.2%, which is higher than the usual 15% found in this kind of study (Hair et al. 2014). Most of the companies were small and medium (54.4%), belonged to the third tier of their SCs (33.0%), and had less than 70% of their suppliers and customers onshore (73.8% and 68.4%, respectively). Regarding respondents, 60.7% of them had more than 5 years of experience and 62.6% played a coordinator or supervisor role in their companies.

Table 1. Sample characteristics ($n = 206$).

Size			Industry sector		
≤ 500 employees	112	54.4%	Metal-mechanics	18	8.7%
> 500 employees	94	45.6%	Automotive	17	8.3%
Tier level	Pharmaceutical	17	8.3%		
1st tier	45	21.9%	Food & beverage	16	7.8%
2nd tier	53	25.7%	Electronic	16	7.8%
3rd tier	68	33.0%	Textile, clothing & footwear	16	7.8%
4th tier	40	19.4%	Furniture & household goods	15	7.3%
% of onshore suppliers	Tobacco	15	7.3%		
< 70%	152	73.8%	Chemical	14	6.7%
≥ 70%	54	26.2%	Oil & gas	13	6.3%
% of onshore customers	Personal care & hygiene products	13	6.3%		
< 70%	141	68.4%	Machinery & equipment	12	5.8%
≥ 70%	65	31.6%	Wood, pulp & paper products	12	5.8%
Respondent experience	Others	12	5.8%		
≤ 5 years	81	39.3%	Respondent role		
> 5 years	125	60.7%	Manager or director	77	37.4%
			Coordinator or supervisor	129	62.6%

3.2. Bias countermeasures

Whenever psychometric scales are utilised to check respondents' opinions, there may be certain kind of bias. To minimise this issue, we conducted a number of countermeasures that helped ensure the validity of our questionnaire and the collected data. First, since the survey was conducted online, we designed the questionnaire to show respondents one part at a time. Hence, respondents could not see the subsequent parts of the questionnaire as they responded it. This created enough dissociation between parts, helping mitigating bias (Podsakoff and Organ 1986). Initial statements were also inserted to inform respondents about the anonymity and confidentiality of the study, and the absence of right or wrong answers (Podsakoff et al. 2003). To check for non-response bias between early ($n = 121$) and late ($n = 85$) respondents, Levene's test for equality of variances and a t-test for equality of means were employed (Armstrong and Overton 1977). As no significant differences in means and variances between groups were found, this issue was disregarded.

Finally, we adopted Harman's single-factor test with an exploratory factor analysis to verify common method bias (Malhotra, Birks, and Wills 2006). The test involving all variables resulted in a first factor that accounted for 25.71% of the total variance. Since we did not find a single factor explaining most of the variance (i.e. > 50%; Hair et al. 2014), common method bias issues were not considered.

3.3. Data analysis

The data analysis consisted of three main steps. In the first step, we conducted a clustering analysis of observations based on the levels of AI PU and AI PEOU to group firms with similar attributes in clusters. Cluster analyses to group firms with similar attributes has been an accepted statistical technical in the supply chain literature (Malik et al. 2019). For that, we initially applied Ward's hierarchical method to properly identify the number k of clusters through the assessment of the dendrogram (Gordon 1999). Observations of the clustering variables yielded four clusters, as displayed in Figure 3. Then, we refined the clustering analysis utilising the non-hierarchical k-means method (Rencher 2002), and setting k equals to 4. To verify validity of the rearranged clusters (see Appendix B), we carried out an analysis of variance (ANOVA), which indicated that the means of the clustering variables in each cluster were significantly different (p-values < 0.05). 49 observations were assigned to cluster #1, which was characterised by lower mean values for both AI PU and AI PEOU. Cluster #2, comprised of 38 respondents, denoted a lower mean for AI PU but a higher mean for AI PEOU. In opposition, observations in cluster #3 ($n_3 = 75$) had a higher mean value for AI PU and lower one

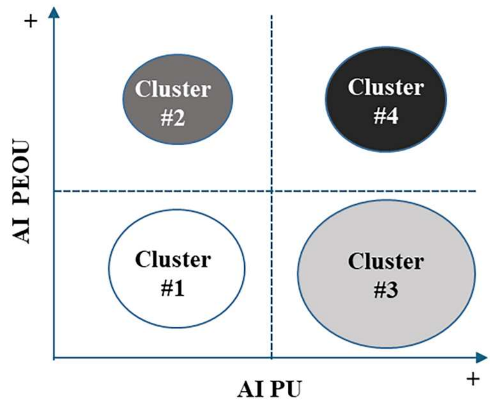

Figure 3. Illustration of clusters.

for AI PEOU. Finally, cluster #4 ($n_4 = 44$) consisted of observations in which both AI PU and AI PEOU had high mean values.

In the second step, we assessed the four clusters' composition to identify their main characteristics (i.e. company size, tier level, and onshore suppliers and customers). For that, we verified whether the distribution frequency of each characteristic across clusters was different utilising the Pearson's chi-squared test (Tabachnick and Fidell 2013). Adjusted residuals larger than $|1.96|$ were utilised to verify significant differences (p-value < 0.05). It is worth mentioning that, due to the industry sector diversity and data scattering existing in the study sample, the frequency analysis was not undertaken with industry sector, as the number of observations for each sector across clusters was lower than 5 in most cases (Hair et al. 2014).

The third step consisted of another round of ANOVA to compare the mean values across clusters for both SCL dimensions: driver and network. Comparisons whose F-values were significant (p-value < 0.05) had their pairwise relationship assessed in terms of differences of means (Tabachnick and Fidell 2013). This final step aimed to check whether the SCL dimensions could significantly vary when the levels of AI PU and AI PEOU changed.

4. Results

Table 2 reports the results for the clusters composition. Cluster #3 (high AI PU – low AI PEOU) is the largest group (75 firms, 36.4% of the sample) and is composed of those companies that perceive a high usefulness of IA but find it difficult to use. Cluster #2 (low AI PU – high AI PEOU) is the least numerous group (38 firms, 18.4% of the sample) and it is made up of those companies that perceive little utility in the use of IA but consider it to be easy to use. The clusters detected could be in line with the innovation diffusion cycle (Rogers 1962), and cluster #4 (high AI PU – high AI PEOU) could be assimilated to the group of innovators and early adopters. Those companies that do not perceive the usefulness and ease of use of AI (cluster #1 – low AI PU – low AI PEOU) will probably be part of the group of companies lagging behind in the adoption of the technology (skeptics). On the other hand, companies that perceive the usefulness of AI, but consider it difficult to use (cluster 3), will find the appropriate training to implement it. They are seen as the pragmatists who will make up the early majority. Finally, those companies that see little utility in the use of AI, but perceive it as easy to use (cluster #2), will need evidence to move them towards its implementation, so they will probably be positioned in the group of conservatives configuring a late majority in the use of AI.

Analysing the clusters by the variables that characterise the sample, company size seemed to show significant differences in clusters #1 (low AI PU – low AI PEOU) and #4 (high AI PU –

Table 2. Clusters composition analysis.

Characteristic		Cluster #1 ($n_1 = 49$) Low AI PU – Low AI PEOU		Cluster #2 ($n_2 = 38$) Low AI PU – High AI PEOU		Cluster #3 ($n_3 = 75$) High AI PU – Low AI PEOU		Cluster #4 ($n_4 = 44$) High AI PU – High AI PEOU		Pearson χ^2
		Frequency	%	Frequency	%	Frequency	%	Frequency	%	
Size	≤ 500 employees	***35***	31.3%	20	17.9%	43	38.4%	14	12.5%	8.758*
	> 500 employees	14	14.9%	18	19.1%	32	34.0%	***30***	31.9%	
Tier level	1st	10	22.2%	8	17.8%	13	28.9%	14	31.1%	7.621*
	2nd	15	28.3%	6	11.3%	23	43.4%	9	17.0%	
	3rd	19	27.9%	11	16.2%	26	38.2%	12	17.6%	
	4th	***5***	12.5%	13	32.5%	13	32.5%	9	22.5%	
% of onshore suppliers	< 70%	***37***	24.3%	21	13.8%	***54***	35.5%	***40***	26.3%	34.520**
	≥ 70%	12	22.2%	17	31.5%	21	38.9%	4	7.4%	
% of onshore customers	< 70%	29	20.6%	***30***	21.3%	47	33.3%	***35***	24.8%	25.921**
	≥ 70%	20	30.8%	8	12.3%	28	43.1%	9	13.8%	

Notes: * p-value < 0.05. ** p-value < 0.01. Values in italic and bold are statistically different in the comparison across clusters, i.e. adjusted residuals larger than |1.96|.

high AI PEOU). Smaller companies appear to more frequently perceive both AI's usefulness and ease-of-use at lower levels (cluster #1), whereas larger companies more frequently perceived them at higher levels (cluster #4). Large companies, which *a priori* will have more consolidated learning strategies, are mostly located in clusters #3 and #4 (34% and 31.9%, respectively). Therefore, a total of 65.9% of the large firms in the sample manifest a high AI PU, i.e. they recognise the usefulness of AI, although some of them consider its use difficult, and a total of 48.9% consider that the perceived ease to use is low.

No significant differences in frequencies across clusters was observed when considering tier levels, except for 4th tier companies in cluster #1 whose frequency was significantly lower (adjusted residual = −2.2; p-value < 0.05) than the others. For onshore suppliers, companies whose percentage was below 70% were predominantly more frequent in clusters #1, #3 (high AI PU – low AI PEOU), and #4. Instead, companies with less than 70% of its customers onshore were significantly more frequent in clusters #2 (low AI PU – high AI PEOU) and #4. However, cluster #4 presents the lowest percentages of onshore suppliers and customers ≥ 70% (7.4% and 13.8%, respectively). Only 4 (9.1%) and 9 (20.5%) of the 44 firms in cluster #4 have ≥ 70% onshore suppliers and customers, respectively. Cluster #2 has a similar percentage of onshore customers ≥ 70%, 8 out of 38 firms (21%) but its percentage of onshore suppliers ≥ 70% is 44.7% (17 out of 38 firms). Companies in cluster #4 (68.2% large firms) have a profile with a higher percentage of offshore suppliers and customers. Therefore, coordination and alignment between companies, and SC integration in general, are more complex than in the other clusters. The companies in cluster #2 (47.4% large firms) have a similar situation in terms of offshore suppliers but have a lower percentage of offshore customers. This will probably lead to easier upstream coordination and integration, given the closer proximity to suppliers than to customers. Finally, companies in clusters #1 and #3 have a similar profile in terms of the percentage of suppliers (75.5% and 72% are < 70% onshore, respectively) and customers (59.2% and 62.7% are < 70% onshore, respectively) onshore. Therefore, they are the clusters with the highest percentage of onshore customers ≥ 70%, which tends to facilitate coordination and downstream integration.

Table 3 shows the ANOVA results for the SCL dimensions across clusters. Similar trends in results were observed regardless of whether the relationship was between the focal company and its suppliers or between the focal company and its customers. Such a similarity in results supports the discussion of SCL from a more holistic perspective, without necessarily discriminating the relationship between the focal company and its suppliers or customers. To facilitate the comprehension of these results, Figure 4 schematically illustrates them.

5. Discussion

As can be observed in Figure 4, when the perception about AI's usefulness and ease-of-use are both low (cluster #1), lower mean values were obtained for both SCL driver and network. Although AI tools may be deemed as very versatile and disruptive (Cao et al. 2021; Riahi et al. 2021), companies from this cluster seem to struggle with its potential applications either with their suppliers or customers. According to TAM assumptions (Davis 1989), lower levels of PU and PEOU might result in a poor AI usage. AI tools arguably are an enabler for better decision-making processes in SCs (Soleimani 2018), and their poor utilisation might restrict the achievement of a broader collaboration and trust among SC players. This may impair the development of more collective efforts to generate and share knowledge within and across SCs (Bessant 2004; Biotto, De Toni, and Nonino 2012), leading to learning initiatives centralised by companies that exert influence on the SC.

According to connectivism learning theory (Downes 2010;; Duke, Harper, and Johnston 2013 Siemens 2005), decision-making is part of the learning process, so that what SC players currently know might affect future decisions. Nevertheless, while there appears to be a right answer now, this decision may not be correct later due to the constantly information change. Consequently, organisations from this cluster, which have more conservative views on AI, tend to have their

Table 3. ANOVA results.

SCL dimensions		Cluster #1 Low AI PU – Low AI PEOU		Cluster #2 Low AI PU – High AI PEOU		Cluster #3 High AI PU – Low AI PEOU		Cluster #4 High AI PU – High AI PEOU		ANOVA *F*-value	Pairwise comparison [a]
		Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.		
Relationship between focal c ompany and suppliers	SCL driver	1.94	0.91	3.11	1.15	2.05	1.04	3.03	1.29	17.88**	#1 < #2; #2 > #3; #1 < #4; #3 < #4
	SCL network	2.01	0.84	1.95	0.76	3.15	1.25	3.10	0.99	9.56**	#1 < #3; #2 < #3; #1 < #4; #2 < #4
Relationship between focal c ompany and customers	SCL driver	1.87	1.01	2.88	1.03	1.99	1.12	2.95	1.22	10.86**	#1 < #2; #2 > #3; #1 < #4; #3 < #4
	SCL network	1.74	0.88	1.83	0.90	3.28	1.18	3.13	1.30	13.75**	#1 < #3; #2 < #3; #1 < #4; #2 < #4

Notes: * p-value < 0.05. ** p-value < 0.01. [a] Only significant pairwise differences (p-value < 0.05) displayed.

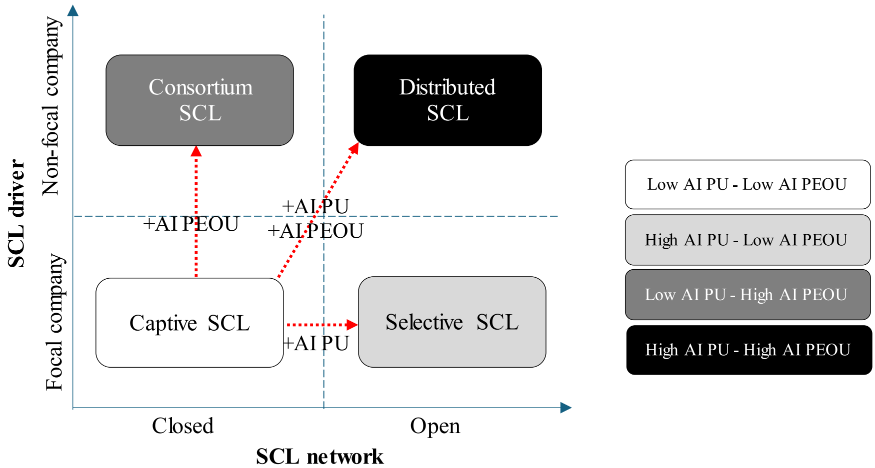

Figure 4. Representation of SCL types according to AI PU and AI PEOU.

learning initiatives more restricted. Related to the four elements that distinguish a knowledge-generating network from a mere set of connected elements in the connectivism theory (Downes 2012), this cluster could be considered as the one with the least connectivist dynamic (autonomy, diversity, openness and connectivity). Based on this evidence, we argue that SCL tends to be driven by the focal company through a more closed network, denoted as *captive SCL*, when both AI PU and AI PEOU are low.

In opposition, when both AI PU and AI PEOU are high (cluster #4), the mean values for both SCL dimensions significantly increase (p-value < 0.05). In other words, when companies truly understand the benefits of AI adoption to support their relationships with both suppliers and customers and believe that the complexity of such AI tools is not an issue, learning efforts are prone to be led by multiple players in a cross-SC approach; characterising a *distributed SCL* (Silvestre et al. 2023). It involves learning efforts led by non-focal players across a network comprising players from various SCs, facilitating knowledge dissemination and leading to a more collaborative approach, as observed in more innovative industry sectors such as information and technology-oriented industries.

Following the concepts from the connectivism learning theory, this may enhance the learning network by increasing the number of nodes (represented by SC players) and creating new connections (represented by the extent of knowledge sharing) (Şahin 2012), helping learning occur more dynamically. Consequently, this cluster has the most connectivist dynamic (autonomy, diversity, openness and connectivity) and it could be considered as a high-level knowledge-generating network. Following connectivism assumption, well-connected knowledge enables more learning. Previous studies (e.g. Helo and Hao 2022; Pournader et al. 2021) indicated that a more pervasive and extensive use of AI across the SC might lead to benefits that go beyond the desired operational improvements, such as increase in vertical and horizontal collaboration, and facilitated knowledge management and transfer. Since higher levels of AI PU and AI PEOU tend to yield a high AI utilisation (Davis, Bagozzi, and Warshaw 1989), those collateral benefits may democratise and legitimate learning across multiple SCs.

When only AI's ease-of-use is highly perceived, but its usefulness is not extensively perceived (cluster #2), there seems to occur a significant increase in the mean values for SCL driver while the ones for SCL network remain low. Although respondents from this cluster may not deem AI's usefulness as highly as others, they acknowledge that its application in the SC may not be so difficult. According to the report from Butner (2017), many senior managers recognise that AI's ease-of-use may raise the pervasiveness of its applications in the next years. Such an AI pervasiveness might promote innovation in many tiers of the SC, which can encourage different SC players to take the lead on learning initiatives (Knoppen, Christiaanse, and Huysman 2010).

From the perspective of the connectivism learning theory, learning may be seen as actionable knowledge that goes beyond the individual organisation, relying on diversity of opinions or data presented in the SC (Kropf 2013). As a non-focal company driven SCL is linked to the SC players' interests, learning may be fostered by AI in different fields and ways that may support the achievement of their strategic and operational objectives (Ali, Nagalingam, and Gurd 2017). However, this might still remain within the SC network, narrowing the knowledge to the boundaries of a single SC and requiring less efforts on governance structures towards a participatory decision-making process (Azadegan and Dooley 2021). These findings suggest that SCL tends to be driven by non-focal companies through a more closed network where knowledge is not shared with actors in others SCs (i.e. a consortium SCL) when AI PU is low and AI PEOU is high. It represents broader stakeholder interests, and the learning efforts are perceived as collective.

When companies perceive AI as highly useful but still consider its use very challenging in the SC (cluster #3), the mean values for SCL driver are lower and a significant increase (p-value < 0.05) is observed for SCL network mean values. This outcome infers that SCL might be driven by the focal company through a more open network, a.k.a. *selective SCL*, when AI PU is high and AI PEOU is low. According to Silvestre et al. (2023), the interests of a focal company are prioritised, and partners are selectively identified from multiple SCs to create and disseminate knowledge. This approach allows to generate synergies and multiply the impacts created by the SCL generation and dissemination in different SCs. This type of SCL usually presents facilitated coordination efforts predominantly led by the focal company (e.g. automakers in the automotive industry) and broader views due to the perspectives from different SCs.

This also tends to more easily nurture and maintain SC connections needed for continual learning (Kropf 2013), enhancing the ability to identify connections between fields, ideas, and concepts that favour more prominent SCL (Kop and Hill 2008). Because the perception on AI's ease-of-use is lower, it is reasonable to expect a resourceful focal company, which has the required skills and infrastructure to extensively adopt AI (Chiu, Zhu, and Corbett 2021; Leyer and Schneider 2021), to drive SCL while both suppliers and customers play a follower role. Nevertheless, a higher perception on AI's usefulness might entail a more extensive implementation on different SC processes of interest of the focal company (e.g. procurement, scheduling, distribution, etc.), affecting several players somewhat related with the focal company but from multiple SCs. In this case, AI tools (e.g. machine learning and natural language processing) would be supporting the generation of knowledge by and diffused to players across SCs, hence, increasing synergy and relevance of learning (Niu and Shen 2022).

Summarising, when both AI PU and AI PEOU are low (cluster #1), SCL tends to be driven by the focal company through a more closed network (i.e. captive SCL) because generally the benefits/skills to use the technology/knowledge are not clear/existent. But if both AI PU and AI PEOU are high (cluster #4), then SCL tends to be driven by multiple players in a cross-SC approach (i.e. distributed SCL) because generally the benefits/skills to use the technology/knowledge are very clear/existent. In the case that AI PU is low and AI PEOU is high (cluster #2), SCL tends to be driven by non-focal companies through a more closed network (i.e. a consortium SCL) often because the usefulness is seen only by a small segment of the companies in the SC, and thus knowledge is not broadly transferred to actors in others SCs. Finally, when AI PU is high and AI PEOU is low (cluster#3) SCL tends to be driven by the focal company through a more open network (i.e. selective SCL) because the technology/knowledge is overall considered as highly useful but considered challenging in terms of its employability.

Overall, the perceptions about AI adoption and the SCL must be structured starting from a strategy that must be aligned with a technology management appropriate to the objectives pursued by the SC. An adequate strategy and technology management present evidence of significant performance improvement that is reinforced by the interaction of both elements (Arana-Solares et al. 2019).

Consequently, the results obtained lay the foundations for future research to develop the relationship between AI, learning mechanisms, SCL types, and performance.

6. Conclusions

In this paper, we investigated the relationship between the perceptions about AI adoption and SCL dimensions using the TAM model and the connectivism learning theory. Our findings were derived from empirical data collected from 206 practitioners who played either top or middle management positions in different industry sectors. Results present a valid contribution to both theory and practice, as indicated below.

6.1. Theoretical implications

From a theoretical standpoint, this study provided evidence to better understand the influence of organisations' perceptions about AI's usefulness and ease-of-use on the way learning is driven and generated/shared in SCs. Since AI is a recent phenomenon whose implications are still under investigation, we utilised the concepts and assumptions preconised by the TAM and connectivism learning theory to verify how different combinations of its PU and PEOU might be associated with SCL dimensions. As AI PU and AI PEOU influence the actual usage of AI in the SC, identifying how SCL dimensions (driver and network) vary according to these perceptions contributes to a more comprehensive digital transformation across SCs. This also builds on the typology of SCL proposed by Silvestre et al. (2023), shedding light on how AI's usefulness and ease-of-use may help promote different types of SCL through the increase on the number of nodes and connections, required to fully achieve a learning SC. For instance, when AI PU and PEOU are both lowly perceived, a captive SCL is likely to be observed minimising their connectivist dynamic (autonomy, diversity, openness and connectivity). In opposition, high levels of AI PU and PEOU tend to lead to a distributed SCL in which connectivist dynamic is also high.

6.2. Practical contributions

In practical terms, the identification of how SCL is affected by organisations' perceptions about AI adoption may help SC managers and practitioners prioritise their digitalisation efforts, adjusting them based on the expectations regarding the four types of SCL. Since SCL driver and network may shift as perceptions about AI adoption vary across multiple SC tiers and industry sectors, managers might promote specific learning strategies that contribute to a greater awareness about AI adoption, potentially moving the learning features in their SCs and leading to superior operational performance results. This supports the development of more assertive decision-making processes and effective problem-solving initiatives. As learning is usually a time-consuming process, the anticipation to potential issues that may impair it in the SC may result in competitive advantages not only for the single (focal) company but also to players from the same or different SCs. Therefore, the identification of the influence of organisations' perceptions about AI adoption on SCL offers arguments to design long-term AI-based SCL initiatives that support key strategic goals. Following the connectivism theory, if managers seek learning-oriented networks, they must design the SC with a view to improving its connectivity, openness, autonomy of the SC partners and diversity of points of view. This is a unique contribution of our study, as we are not aware of any similar investigation.

6.3. Limitations and future research

This work has some limitations that must be mentioned. First, with regards to its methodological approach and data collection, we utilised single respondents' opinions to verify the behaviour of a phenomenon that essentially occurs across multiple SC players. Although we performed all countermeasures to avoid any kind of bias, we are aware of the limitations of our approach. In this sense, future studies could encompass different methodologies (e.g. longitudinal case studies) to confirm our findings and check their validity.

Additionally, we did not collect information on the performance of the surveyed companies and their respective SCs. Therefore, although previous works suggested a positive relationship between SCL and operational performance, we cannot affirm that such a relationship remains the same when AI is introduced. Hence, there is the need to include SC performance as part of future studies on the topic. It should be also considered that the study was focused on Brazilian companies, so results reflect the situation in the context considered. Consequently, we should be cautious in extrapolating the results to other countries with different socioeconomic circumstances. Therefore, conducting this study in other countries and sectors would allow us to generate new evidence on the topic under research.

Finally, as most SCs are still undergoing the AI adoption, the tools and processes being explored significantly vary between focal companies, and their suppliers and customers. Due to this fact, we kept our investigation quite broad, not specifying any application or SC process in the survey. The consideration and control of specific AI applications in SCs could offer more insightful results to how learning is affected, raising additional contributions to both practice and theory. Another limitation refers to the fact that we assessed respondents' perceptions about AI PU and PEOU instead of AI's actual adoption level. Although PU and PEOU might directly influence the usage of AI, we could not verify the actual impact of AI adoption on SCL. Further studies can build on ours to explore the relationship between AI adoption and SCL. In line with this limitation, the adoption of other technologies may have different implications on SCL. For instance, while blockchain may affect the way organisations relate due to increased transparency, digital twins can help SC players simulate real situations and their outcomes enabling them to make better decisions. Although we were very careful to only indicate conclusions that were fully supported by our findings, we understand future research could encompass the impact of other technologies and specific AI applications on SCL.

Data availability

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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