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Dynamics between blockchain adoption determinants and supply chain performance: An empirical investigation

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ABSTRACT

The logistics and supply chain management (SCM) field is experimenting with the integration of blockchain, a cutting-edge, and highly disruptive technology. Yet, blockchain is still nascent, and the extant literature on this technology is scarce, especially as regards the relationship between blockchain and SCM. Additionally, existing studies have not yet addressed sufficiently the enablers of blockchain adoption and the interplay with supply chain performance. In order to reduce this gap, this study aims to examine the potential influence of blockchain on supply chain performance. We draw on the literature on technology adoption and supply chain performance, as well as on the emerging blockchain literature, to develop and test a model in two countries, namely India and the US. Accordingly, we administered a survey in order to review the opinions and views of supply chain practitioners. The results support the model and indicate that blockchain applications can improve supply chain performance. In particular, our findings suggest that knowledge sharing and trading partner pressure play an important role in blockchain adoption, and that supply chain performance is significantly influenced by supply chain transparency and blockchain transparency. Another finding was the inexistence of evidence for a moderation effect of the industry variable on the outcomes. The research conclusions have substantial managerial and theoretical implications. Our model contributes mainly to the theoretical advancement of SCM-blockchain, thus allowing scholars to adapt our validated model.

1. Introduction

The logistics and supply chain management (SCM) field recently went through unprecedented disruptions (Büyüközkan and Göçer, 2018), thanks to the development of information and communications technologies (ICTs) (Harris et al., 2015; Frank et al., 2019; Chen, 2019; Goldsby and Zinn, 2016; Schniederjans et al., 2019). Blockchain is one of these disruptive ICTs (Kshetri, 2017a) that could have huge impacts on operations, supply chain and business models (Azzi et al., 2019; Banerjee, 2018; Chang et al., 2019; Dolgui et al., 2019; Helo and Hao, 2019; Longo et al., 2019; Schmidt and Wagner, 2019), and facilitate the execution of smart contracts between supply chain stakeholders (Dolgui et al., 2019). Indeed, blockchain technologies allow the digitalization of decentralized business models through the "implementation of autonomous algorithmic trust controls for decentralized systems" (Gartner, 2019).

Available studies have made it clear that blockchain technologies (Helo and Hao, 2019; Helo and Shamsuzzoha, 2020; Kamble et al., 2020; Wang et al., 2019; Aste et al., 2017; Y. Chen, 2018; Kshetri, 2018; Viryasitavat et al., 2018) have the potential to transform almost all SCM business models, enhance end-to-end supply chain business processes and thus improve supply chain performance. Also, blockchain could facilitate the access to product or service, thereby influencing customer perceived value of the said product or service (Morkunas et al., 2019). Considering the blockchain tamper-proof characteristic and the impact it may create in the area of logistics and supply chain (Aste et al., 2017; Viryasitavat et al., 2018), the level of blockchain adoption in this field is expected to increase significantly in order to enhance supply chain performance.

Amongst other advantages, blockchain technologies can improve complex supply chain problems (e.g., product safety, supply chain visibility, transparency, etc.), and enhance the traceability of operations (Helo and Shamsuzzoha, 2020; Chang et al., 2019; Saberi et al., 2019; Islam et al., 2018; Jeppsson and Olsson, 2017), irrespective of the area

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involved: food safety (Tian, 2017) and security (Saberi et al., 2019), wine industry (Biswas et al., 2017), healthcare (Benchoufi et al., 2017), e-commerce platform (Ying et al., 2018), and so forth. In the supply chain contexts, blockchain is recognized as a disruptive technology (Choi et al., 2019) that can efficiently solve complex issues such as transparency and accountability (Biswas et al., 2017; Francisco and Swanson, 2018; Kshetri, 2018; Zou et al., 2018), security (Xu et al., 2018; Rahmanzadeh et al., 2019), resilience (Xu et al., 2018), the search for trust (Kano and Nakajima, 2018; Reyna et al., 2018), uncertainty (Kim and Laskowski, 2017), fraud prevention (R. Y. Chen, 2018), confidence (Lu and Xu, 2017), and product recalls (Kshetri, 2017b), and the reduction of supply chain costs (Roeck et al., 2019), etc. Thus, integrating blockchain technology with supply chains is a robust and trusted approach for supporting and remodeling the supply chain patterns and upgrading the level of service delivery. Moreover, blockchain could be an appropriate means of achieving supply chain sustainability (Saberi et al., 2019).

While these recent studies have emphasized blockchain benefits in the supply chain field, effective applications of this technology are still in their infancy (Babich and Hilary, 2020; Queiroz et al., 2019; Schmidt and Wagner, 2019), as prior literature does not point blockchain as an enabler of supply chain performance and other features (e.g., trading partner readiness and pressure, knowledge sharing, diffusion, transparency). For example, a recent review study on bitcoin, blockchain and Fintech in the supply chain, (Fosso Wamba et al., 2018), identified very few empirical studies on these topics. Therefore, our study aims to bridge the knowledge gap identified in the literature by unlocking the value that blockchain can add to supply chain performance, and exploring cultural differences between countries. That is, this study primarily seeks to examine the antecedents of blockchain adoption, and its influence not only on supply chain transparency and blockchain transparency, but also on supply chain performance. Following previous studies on technology adoption which found important differences between countries (Fosso Wamba et al., 2016; Venkatesh and Zhang, 2014), we look forward to exploring any potential differences in blockchain adoption between countries. Therefore, the following research questions need to be addressed:

1. Is blockchain an effective technology to support supply chain performance?
2. Are there any differences in blockchain adoption behavior in supply chains across countries?

In order to answer these research questions, this study draws on the emerging literature on blockchain technologies, on the integration of blockchain with supply chain and on technology adoption to develop a research model that investigates the relationship between blockchain and supply chain performance. The model is tested using data collected in India and the US. In terms of contribution, the findings of this study should enrich not only the literature on logistics and SCM but also the emerging literature on the blockchain. From the managerial perspective, our proposed model contributes to enhancing the understanding of relationships between blockchain variables and supply chain performance, while imposing consideration for countries' particularities in these relationships. From the theoretical lens, our model was validated by the strong results obtained, and this opened up opportunities for an in-depth analysis of such relationships. In addition, our model may serve as a starting-point for other studies on blockchain in logistics and SCM.

The rest of this paper is organized as follows. The theoretical foundation for the theory and constructs of interest is explained, which leads to the formulation of hypotheses and the research model. The next step is the description of the method used to evaluate the model, followed by the results and findings. Then, there is a discussion of results, which involves managerial and theoretical implications. Research limitations and future research avenues are finally presented before the main conclusions of this study are drawn.

2. Theoretical foundation

Supply chain performance plays a critical role in all types of organizations, and attaining such performance has been rendered more difficult by the increased complexity of operations in the digital age. With the integration of blockchain, we deemed it necessary to map the gaps and enable a better understanding of the relationship between blockchain and supply chain performance, so we revisited the extant literature concerning supply chain, blockchain and other technologies in order to acquire more insights.

2.1. Technology adoption models

In this study, we have adopted an approach that is centered on blockchain adoption. This means that we provide the antecedents of adoption and all that comes up after adoption, including benefits for the supply chain. In the first place, we lay the groundwork about the literature on technology adoption (Davis et al., 1989; Warshaw and Davis, 1985). An important contribution was provided by Davis (1989), who presented two basic constructs that predict technology adoption and usage at the individual level. Is the two constructs are known as key elements of the technology acceptance model (TAM). These basic constructs are the perceived usefulness (PU) and the perceived ease of use (PEOU). Over the last 30 years, various models were proposed based on these roots (Venkatesh et al., 2012, 2003; Venkatesh and Davis, 2000; Venkatesh and Zhang, 2014).

Moreover, Venkatesh et al. (2003) extended the main basis of the TAM and even included seven more related theories about user behavior, in order to obtain a widespread and influential model called the unified theory of acceptance and use of technology (UTAUT). This model has four basic constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions). But other elements such as gender, age, experience, and voluntariness of use are variables that act as moderators of the model (Venkatesh et al., 2003). Since then, other influential studies using or reexamining a modified version of the original UTAUT (Dwivedi et al., 2017a) (Dwivedi et al., 2017b) have been published. Besides, the extension of the UTAUT, namely UTAUT2—wich incorporates three constructs (hedonic motivation, price value, and habit) (Venkatesh et al., 2012)—has been widely used in and adapted to a good number of contexts (Alalwan et al., 2017; Farooq et al., 2017; Makanyeza and Mutambayashata, 2018).

Kamble et al. (2018) recently used the TAM constructs in Indian supply chains in order to understand the behavior about blockchain adoption. The authors showed that PEOU was a good predictor of the PU, which in turn achieved a strong power of predicting the intention to use blockchain. Based on the characteristics of the models mentioned above (TAM and UTAUT), we proposed a model that captures blockchain adoption and the impacts of blockchain on supply chain performance. Before describing the conceptual model, we have chosen to analyze some basic features of blockchain, as well as its interplay with supply chain performance. More recently, Wong et al. (2019) proposed an adaptation of the well-known Technology, the Organisation and Environment (TOE) Framework, to investigate the adoption of blockchain in operations and supply chain management (OSCM) by Malaysian Small-Medium Enterprises. The authors found that complexity, cost, relative advantage, and competitive pressure had a significant influence on the intention to adopt blockchain.

2.2. Blockchain applications: fundamentals

Blockchain technology emerged in the cryptocurrency market (Nakamoto, 2008) over a decade ago. The blockchain core is related to a distributed database (ledgers) (Babich and Hilary, 2020; Kano and Nakajima, 2018; Schmidt and Wagner, 2019) that performs in a shared and synchronized environment (chain), in which information is validated by the users (Aste et al., 2017). We have chosen to follow the following definition by Risius and Spohrer (2017):

Blockchain technology refers to a fully distributed system for cryptographically capturing and storing a consistent, immutable, linear event log of transactions between networked actors. This is functionally similar to a distributed ledger that is consensually kept, updated, and validated by the parties involved in all the transactions within a network. In such a network, blockchain technology enforces transparency and guarantees eventual, system-wide consensus on the validity of an entire history of transactions (Risius and Spohrer, 2017, p. 386).

This definition implies that, in a decentralized system, once transactions are validated, alterations are no longer possible (Y. Chen, 2018), and that there is a generation of the tamper-proof characteristic of blockchains. Moreover, all transactions are traceable, thereby giving organizations the possibility to achieve the genesis node. In essence, the data are organized into blocks that shape a chain (Li et al., 2018) and the current block and store the information of the previous.

Blockchain applications have the potential to remodel and enhance the performance of the traceability process through the entire SCM (Behnke and Janssen, 2019; Kamble et al., 2019). For instance, in the food supply chain (Dabbene et al., 2014; Pizzuti and Mirabelli, 2015; Tian, 2017), they indicate the origin of all nodes, and this has triggered organizations to invest heavily in systems to improve provenance traceability. Recently, Thakur et al. (2019) showed an exciting blockchain application that is adopted and used for land titling in India. The authors highlighted the existence of several challenges regarding the implementation of blockchain-like internet infrastructure. Moreover, it is well acknowledged that blockchain technologies are able to efficiently support node provenance (Biswas et al., 2017; Kim and Laskowski, 2018), thus facilitating information sharing across the SC environment and improving the decision-making process. Furthermore, blockchain technologies are expected to bring strong changes to global SCM (Hughes et al., 2019), while reconfiguring the role of intermediaries in supply chains (Tönnissen and Teuteberg, 2019). As emerging economies are increasing adopting such technologies, they can support and render more efficient the exploration of global supply chains (Schuetz and Venkatesh, 2019) while enhancing financial inclusion.

2.3. Supply chain performance as a result of blockchain integration: an overview

Our study follows previous studies that considered the supply chain as a complex network composed of nodes and links (Borgatti and LI, 2009; Carter et al., 2015; Choi and Dooley, 2009). In this context, supply chain networks can be viewed as a complex adaptive system (Choi et al., 2001) that needs information resulting from processed data in order to support organizations' decision-making processes for improved performance. A recent study by Pan et al. (2019) found that organizations could implement blockchain to achieve improved performance on sales costs and, ultimately, create an impact on supply chain performance. Therefore, the recent literature fully agree on the potential of the blockchain technologies to transform the operations and supply chains (Azzi et al., 2019; Banerjee, 2018; Helo and Hao, 2019; Helo and Shamsuzzoha, 2020). Several benefits of blockchain, when applied in operations and supply chain, can be achieved. For instance, blockchain technologies lead to real-time traceability (Helo and Shamsuzzoha, 2020), improved transparency between supply chain members (Banerjee, 2018), reduced risks of counterfeiting and more efficiency in supply chain processes (Azzi et al., 2019). In addition, blockchain can improve and bring innovations to all manufacturing supply chains (Abeyratne and Monfared, 2016). This means that with blockchain technologies, supply chain operations in any sector can be improved, together with several other benefits like the minimization of cost transactions, more product visibility due to empowered traceability, and accountability to the supply chain members, etc. As a result, supply chain performance is positively impacted.

In this study, supply chain performance is defined as "the efficient and effective execution of supply chain tasks" (Autry et al., 2014: 57). The literature on business logistics and supply chain management shows that considerable efforts have been put into deeper the understanding of supply chain performance behavior (Datta, 2017; Gligor, 2014; Grawe et al., 2011; Hollos et al., 2012; Singh, 2015; Xu and Dong, 2004; Zhu et al., 2018). A good number of scholars have found significant relationships between supply chain performance and other key variables, and have noted that these relationships affect the SCM. Such relationships are the relationship that is recognized to exist between knowledge exchange and logistics innovation, and the one between logistics innovation and performance (Grawe et al., 2015), with consideration for the boundary between service providers and customers.

Recently, White (2017) employed a Delphi study in order to understand the impact of different types of blockchain in business. The author found that blockchain could improve performance in transactions between partners. In a study of blockchain in the agriculture supply chain, Kamble et al. (2019) found several enablers that can be brought about by blockchain for increased performance: transparency, traceability, lead times reduction, among others. According to Wang et al. (2018), the benefits of blockchain in supply chains span expanded visibility, improved data security, and disintermediation, etc. All these benefits can impact performance. Besides, Wang et al. (2019) emphasized the potential of blockchain technologies to support operational improvement in supply chains, thus impacting on performance.

Additionally, SCM performance was investigated while considering various risk dimensions (Wagner and Bode, 2008), and findings showed that supply chain performance can be affected negatively by supply chain risks. Thanks to blockchain, supply chain risks can be mitigated (Kshetri, 2018; Tian, 2017), together with uncertainties and other irregularities. Blockchain's features that can mostly come into play here are the tamperproof nature of any transaction with blockchain and the ability to create and foster transparency, accountability, traceability and decentralization.

Also, in line with their ability to help understand the supply chain management complexities, blockchain applications are well fitted to eliminate uncertainty (Kim and Laskowski, 2017), and this is all the more important as a high level of uncertainty in the SCM can negatively affect not only a focal organization but the entire network. Considering the complexity of such an environment, SCM performance can be negatively affected (Wagner and Bode, 2008).

Furthermore, blockchain applications play a key role in reducing costs in complex supply chain networks (Kshetri, 2018), but also in ushering in more transparency in the processes, adequate data sharing and information between organizations (Lu and Xu, 2017), cooperation (Aste et al., 2017), as well as trust and efficiency (Kshetri, 2018), among others.

Schmidt and Wagner (2019) recognized the potential of blockchain to minimize transaction costs across the supply chains, reduce opportunistic behavior and increase transparency in the transactions. However, there are some complex challenges to overcome; they are related to privacy, data quality, network effect, and uncertainty. Also, the authors made six robust propositions concerning blockchain, which is as an adequate tool for addressing the above-mentioned issues while enhancing governance through market orientation. In this context, recently, Babich and Hilary (2020) found five key strengths and weaknesses in the interplay between blockchain and operations management. The authors reported strengths such as visibility, aggregation, validation, automation, and resiliency. Weaknesses included the lack of privacy, the lack of standardization, garbage (in/out), the effect of the black box, and inefficiency. Nevertheless, Here, inefficiency resides in the amount of energy that is needed to perform the transactions (in the case of bitcoin). Moreover, is the authors found no evidence of blockchain-enabled network performance as compared to the centralized database.

In the next section, we derive the various hypotheses for this study and further present a conceptual model that will enable us to unlock and gain a better understanding of the relationship between blockchain and supply chain performance. In Appendix A, we follow some of the best practices (Mentzer and Kahn, 1995; Podsakoff et al., 2016) regarding the definitions of constructs. Thus, we followed four steps, namely: (i) searching for the potential definitions; (ii) organizing the said definitions; (iii) formulating the preliminary definition; and (iv) refining the concept.

3. Development of hypotheses and research model

3.1. Knowledge sharing

The organizations' necessity for innovation has been working as an essential driver for improving knowledge sharing (Lin, 2017). In the blockchain-integrated context, knowledge sharing (KS) primarily refers to the exchange of knowledge between firms through their supply chain members. With blockchain, the players of the same supply chain can share real-time information (Tian, 2017), including skills about their common systems and best practices, and how to potentialize the utilization in various SCM processes. KS is concerned with individuals' behaviors when they share information within organizations (Abubakar et al., 2017; Ramayah et al., 2014; Yi, 2009). Therefore, the knowledge involved in KS may be technologies and skills between organizations (Farooq, 2018). From this perspective, we argue that KS between firm partners within the same supply chain is fundamental to blockchain adoption. Therefore, we hypothesize that:

H1. Knowledge sharing has a positive significant effect on blockchain adoption

3.2. Trading partner pressure

A trading partner relationship refers to a business relationship that can involve two or more organizations or organizations and customers. The most common configuration of the trading partner relationship is on the organization-suppliers side. However, the trading partners-customers relationship is also essential (Angeles and Nath, 2000). Considering the supply chain context, these relationships tend to be more complicated, mainly by the number of nodes in the networks. In addition, trading partner readiness can support the optimization of the organization's resource capabilities (Lin, 2006), including as regards saving costs (Holmes and Srivastava, 1999). Furthermore, while trading partner readiness can impact blockchain adoption, pressures can originate from trading partners and others stakeholders (Wang et al., 2010), all of which have the potential of leading to a new technology adoption direction (Hu and Hsu, 2010; Lamming et al., 2001; Tachizawa and Wong, 2014). Previous studies suggest that trading partner pressure is an influential construct for technology adoption (Low et al., 2011; Wang et al., 2010). Therefore, we propose the following hypothesis:

H2. Pressures from trading partners have a positive significant effect on blockchain adoption.

3.3. The role of blockchain adoption and transparency

Blockchain remains a significant technology that organizations have to develop, implement, and manage. It can help integrate different business partners in the SCM, contributing to a more reliable environment (Viryasitavat et al., 2018). With the blockchain technology, organizations can achieve meaningful performance improvement in the supply chain network (Kshetri, 2018), bringing in more transparency (Venkatesh et al., 2016), though it is a complicated subject in several areas and particularly in SCM (Lamming et al., 2001; Morgan et al., 2018; Vorabutra, 2016). In these circumstances, blockchain can increase the level of transparency within the supply chain network (Thakur et al., 2019; Biswas et al., 2017; Francisco and Swanson, 2018; Jeppsson and Olsson, 2017; Lu and Xu, 2017), thereby supporting trust improvement. Thus we hypothesize that:

H3a. Blockchain adoption has a positive significant effect on supply chain transparency.

H3b. Blockchain adoption has a positive significant effect on blockchain transparency.

3.4. The role of blockchain and supply chain performance

The members of a supply chain network exchange a significant amount of data every day. Supply chain performance (Qrunfleh and Tarafdar, 2014) is generally achieved or enhanced with increased complexity, mainly because of the number of available technologies and the issue of information asymmetry. In such circumstances, blockchain technologies are welcome not only to takcle such cases of complexity, but also to promote and improve performance in the OSCM (Hyperledger, 2019; Maersk, 2018) while contributing significantly to new business and revenue streams (Delloite, 2019) (See Appendix B for more details). And given the important number of benefits attributed to blockchain adoption, including accountability improvement (Aste et al., 2017; Biswas et al., 2017; Kshetri, 2018; Zou et al., 2018), this technology is also expected to play a critical role in tackling OSCM challenges such as the need for transparency and trust between members. In terms of traceability SCM gains more accountability and transparency, with a positive effect on all its members. If blockchain can eliminate

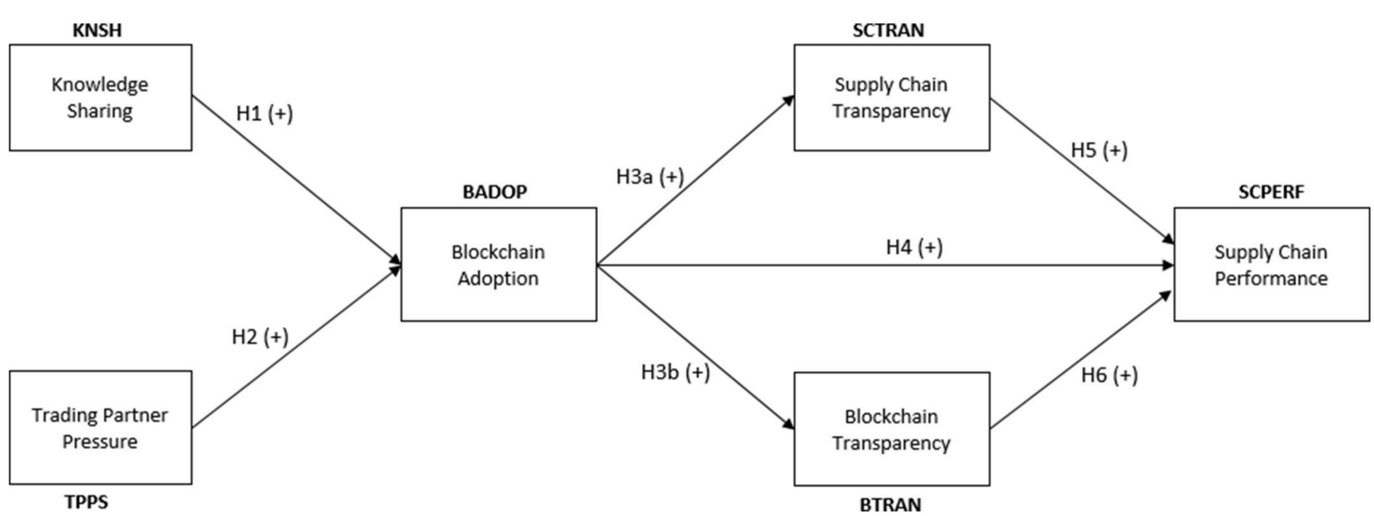

Fig. 1. Conceptual model.

information variability in SCM (Aste et al., 2017), it is evident that trust and cooperation will improve on supply chain performance. This leads us to hypothesize that:

H4. Blockchain adoption has a positive significant effect on supply chain performance.

H5. Supply chain transparency has a positive significant effect on supply chain performance.

H6. Blockchain transparency has a positive significant effect on supply chain performance.

Fig. 1 highlights the conceptual model synthesizing the aforementioned hypotheses and their relationships.

4. Research methodology

4.1. Sampling design and data collection

This study is part of a large project aiming to investigate the adoption, use and impact of blockchain at the firm and supply chain levels (Queiroz and Fosso Wamba, 2019). The data collection was realized through a survey approach. The survey approach is suitable when it comes to investigating a phenomenon that is of interest (in our case, blockchain adoption and its relationship with supply chain performance). Indeed, our sample frame and data collection (Fawcett et al., 2014; Guide Jr. and Ketokivi, 2015; Helmuth et al., 2015) enabled us to better unveil and analyze the characteristics of the phenomenon under study here. Like most recent studies that used a survey method approach to collect data (Dai et al., 2015; Ebad, 2018; Gligor, 2014; Schoenherr et al., 2014), this study added other items from the extant literature and adapted them to fit our research context (Dai et al., 2015).

All constructs were measured by a 7-point Likert scale (ranging from “strongly disagree” to “strongly agree”). The survey was administered by a leading market research firm (http://www.researchnow.com/en-US.aspx), who collected data in India and the US, from supply chain professionals operating in different industries. These participants had at least three years of experience with blockchain-related projects in the SCM field (e.g., interaction with suppliers projects, organization studies to adopt). That is, due diligence was performed to ensure that all participants had some experience with blockchain. All aspects (operational, R&D, plan etc) were concerned with blockchain experience. It is important to note that we applied a survey examining the opinions and views of supply chain practitioners about the adoption of blockchain and its interplay with the supply chain performance. Appendix B highlights some examples of blockchain experience as it can appear in companies. In other words, our informants’ sample met the criterion of rigorousness (Fawcett et al., 2014). Specifically, the sample was made up of 344 valid responses from out of the 974 India-based professionals who agreed to participate in the survey, which gave a response rate of 35.32%. In the US, 6131 professionals took part in the survey, 394 of whom sent valid responses. Here, we obtained a response rate of 6.43%. Table 1 shows the statistics of constructs, while Table 2 reports the respondents’ characteristics.

In terms of gender, the distribution of sample characteristics was similar in the two surveyed countries (India and the US). However, female accounted for approximately 30% of respondents from both countries. The majority of respondents belonged to the age bracket 26–33 (51.2%) in India, against the age bracket 34–41 (39.6%) in the US. Considering the education, the majority of the respondents were holders of a postgraduate degree, that is, 52.6% in India and 33% in the

Table 1
Simple Statistics (pooled data, n = 738).

Item	Mean	sd	Median	Min	Max	Skew	Kurtosis
KNSH1	5.24	1.33	5	1	7	−0.86	0.65
KNSH2	5.28	1.26	5	1	7	−0.84	0.90
KNSH3	5.32	1.26	5	1	7	−0.80	0.77
KNSH4	5.32	1.26	5	1	7	−0.78	0.54
TPPS1	5.26	1.35	5	1	7	−0.94	0.86
TPPS2	5.24	1.32	5	1	7	−0.71	0.27
TPPS3	5.24	1.29	5	1	7	−0.76	0.55
BADOP1	5.33	1.31	6	1	7	−0.91	0.77
BADOP2	5.35	1.26	6	1	7	−0.82	0.75
BADOP3	5.37	1.30	6	1	7	−0.91	0.86
BTRAN1	5.37	1.26	6	1	7	−0.93	1.05
BTRAN2	5.35	1.23	6	1	7	−0.91	1.13
BTRAN3	5.43	1.23	6	1	7	−0.98	1.34
BTRAN4	5.42	1.27	6	1	7	−0.86	0.78
SCTRAN1	5.22	1.32	5	1	7	−0.69	0.33
SCTRAN2	5.22	1.23	5	1	7	−0.53	0.03
SCTRAN3	5.24	1.23	5	1	7	−0.51	0.05
SCTRAN4	5.24	1.22	5	1	7	−0.46	−0.05
SCTRAN5	5.22	1.28	5	1	7	−0.58	0.14
SCPERF1	5.37	1.26	6	1	7	−0.88	0.97
SCPERF2	5.45	1.19	6	1	7	−0.79	0.66
SCPERF3	5.43	1.28	6	1	7	−0.82	0.55
SCPERF4	5.41	1.24	6	1	7	−0.79	0.55
SCPERF5	5.39	1.27	6	1	7	−0.81	0.70
SCPERF6	5.35	1.28	6	1	7	−0.90	1.08
SCPERF7	5.49	1.27	6	1	7	−0.93	1.15
SCPERF8	5.40	1.21	6	1	7	−0.74	0.64
SCPERF9	5.45	1.17	6	1	7	−0.73	0.57
SCPERF10	5.38	1.21	6	1	7	−0.79	0.78

Table 2
Demographic profile (n = 738).

	India		US	
	n	%	n	%
Gender				
Male	241	70.1	285	72.3
Female	103	29.9	109	27.7
Age				
18–25	34	9.9	7	1.8
26–33	176	51.2	84	21.3
34–41	99	28.8	156	39.6
42–49	22	6.4	61	15.5
50+	13	3.8	85	21.6
Highest educational level				
No formal education	0	0.0	2	0.5
Primary	0	0.0	23	5.8
Secondary	5	1.5	36	9.1
Diploma/polytechnic	41	11.9	98	24.9
Bachelor’s degree	117	34.0	105	26.6
Postgraduate degree (Master/Ph.D.)	181	52.6	130	33.0
Number of years working in the organization				
Less than one year	13	3.8	9	2.3
2–5 years	138	40.1	81	20.6
6–10 years	131	38.1	136	34.5
11–15 years	49	14.2	75	19.0
16–20 years	8	2.3	51	12.9
Over 20 years	5	1.5	42	10.7
Industry				
Accommodation and food service activities	5	1.5	15	3.8
Administrative and support service activities	25	7.3	14	3.6
Agriculture, forestry and fishing	4	1.2	8	2.0
Arts, entertainment and recreation	5	1.5	6	1.5
Construction	15	4.4	57	14.5
Education	25	7.3	17	4.3
Electricity, gas, steam and air conditioning supply	12	3.5	11	2.8
Financial and insurance activities	22	6.4	33	8.4
Human health and social work activities	11	3.2	20	5.1
Information and communication	50	14.5	21	5.3
Manufacturing	121	35.2	58	14.7
Mining and quarrying	4	1.2	4	1.0
Professional, scientific and technical activities	18	5.2	21	5.3
Public administration and defense; compulsory social security	0	0.0	2	0.5
Real estate activities	4	1.2	9	2.3
Transportation and storage	15	4.4	64	16.2
Water supply; sewerage, waste management	1	0.3	0	0.0
Wholesale and retail trade; repair of motor vehicles and motorcycles	5	1.5	12	3.0
Other service areas	2	0.6	22	5.6

US. Moreover, the respondents' dominant industry in India was manufacturing (35.2%), whereas, in the US, we had transportation (16.2%), manufacturing (14.7%) and construction with (14.5%).

5. Data analysis

We used a classical structural equation modeling (SEM) (Bollen, 1989) to test the proposed model. All the analyses were performed in R 3.5.1 using the *lavaan* R package, version 0.6–3 (Rosseel, 2012; Rosseel et al., 2019) and the *semTools* R package, version 0.5–1 (Jorgensen et al., 2019). The Maximum Likelihood estimator for SEM requires the data to be multivariate normality. We used the Mardia's multivariate test of normality (Mardia, 1970) to assess the skewness of the data at the pooled and country levels. The Mardia's estimate of multivariate skew equals 173.94 (*p-value* < 0.001) at pooled level, 278.43 (*p-value* $<$ 0.001) for the Indian sample and 270.72 for the US sample (*p-value* $<$ 0.001). The null hypothesis of multivariate normality is rejected both at pooled and country level. As a consequence, we used the robust maximum likelihood (MLM) estimator and the Satorra-Bentler corrected standard errors method (Satorra and Bentler, 1994) to estimate model parameters and their standard errors in the *lavaan* package (Rosseel et al., 2019). MLM adjusts the chi-square (resulting in the Satorra-Bentler corrected chi-square) for its upward bias in the case of nonnormally distributed data (Maydeu-Olivares, 2017).

The fit of the model was evaluated using the Satorra-Bentler chi-square statistic ($SB\chi^2$), the robust comparative fit index (CFI), the robust root mean square error of approximation (RMSEA), and the robust standardized root-mean-square residual (SRMR). Following Hu and Bentler (1999), Steiger (2007), Hooper et al. (2008), and van de Schoot et al. (2012), a model fits the data when CFI $>$ 0.95, RMSEA $<$ 0.06 and SRMR $>$ 0.05. We also reported the *p-value* associated with the null hypothesis of a population RMSEA $<$0.05 and the 90% confidence interval for the Robust RMSEA value.

Cronbach's alpha, and associated confidence interval (Trinchera et al., 2018), was used to measure the internal consistency of each latent variable in the model. Omega Coefficient (Raykov, 2001) and the Average Variance Extracted (AVE) were used to assess the reliability of each construct, while the HTMT approach (Henseler et al., 2015) was used to assess the discriminant validity. In particular, discriminant validity is considered to apply if all the values in the HTMT matrix are smaller than 0.90 (Gold et al., 2001; Teo et al., 2008).

5.1. Common method bias

Common method bias (CMB) (Podsakoff and Organ, 1986) may inflate relations in the model. We tested structural model results for CMB using the post-hoc marker variable approach, as presented by Lindell and Whitney (2001). Following Malhotra et al. (2006), the correlations among the observed variables are adjusted considering the smallest correlation among the observed variables as a proxy for CMB. In Table 3 we compared the structural model parameter estimates obtained after correcting for CMB (i.e. CMB-adjusted estimates) to the original structural model parameter estimates. Path coefficient values and associated significances remained stables after correcting for CMB. We concluded that our model was not affected by CMB.

5.2. Validation of the measurement model

Cronbach's alpha and construct reliability were higher than 0.86 for all the constructs in the model (see Table 4). Moreover, the lower bounds of the confidence intervals computed for the Cronbach's alpha were largely higher than the 0.70 threshold commonly used to verify the reliability of a scale (Nunnally, 1978). The scales used to measure our constructs were all highly reliable.

Our model perfectly fitted the data at pooled level ($n = 738$). All the fit indexes showed an excellent fit ($SB\chi2 = 560.70$ with 369 df; Robust CFI = 0.98; SRMR = 0.03; Robust RMSEA = 0.03; RMSEA $<$ 0.05; and 95% CI [0.02; 0.03]).

Factor loadings are reported in Appendix C. All the loadings were higher than the 0.80 cut-offs (Fornell and Larcker, 1981) and the AVE values in Table 4 were higher than 0.60, indicating an excellent convergent validity (Fornell and Larcker, 1981; Hajli et al., 2017) for all the constructs in the model. The correlation between the latent variables (in Table 5) and the results of the HTMT approach (in Table 6) supported discriminant validity: HTMT values were all smaller than the 0.90 threshold (Gold et al., 2001; Teo et al., 2008).

Table 3
Path coefficients before and after correcting for CMB (pooled results).

Hypotheses	Path	Original estimates	CMB adjusted estimates (r_M = 0.426)
H1	KNSH– > BADOP	0.576***	0.562***
H2	TPPS– > BADOP	0.342***	0.373***
H3a	BADOP– > SCTRAN	0.798***	0.823***
H3b	BADOP– > BTRAN	0.832***	0.892***
H4	BADOP– > SCPERF	0.253**	0.245*
H5	SCTRAN– > SCPERF	0.343***	0.360***
H6	BTRAN– > SCPERF	0.385***	0.384***

Notes: r_M. shared correlation resulting from CMB using the correlation between SCTRAN4 and KNSH3 as marker variable. *p < 0.05; **p < 0.01; ***p < 0.001.

5.3. Validation of the structural model

Strutural model results obtained on the pooled data are reported in Table 7. According to these results, all the research hypotheses are verified at a significance level <0.01. In particular, our results support the hypothesis of a direct, positive impact of KNSH ($\beta = 0.576$, *p-value* $<$ 0.001) and TPPS ($\beta = 0.342$, *p-value* $<$ 0.001) on BADOP. Hypotheses H3a and H3b are also verified: BADOP significanlty and positively impacts on both SCTRAN ($\beta = 0.798$, *p-value* $<$ 0.001) and BTRAN (β = 0.832, *p-value* $<$ 0.001). To conclude, our data support the positive and direct effect of BADOP ($\beta = 0.253$, *p-value* $= 0.006$), SCTRAN ($\beta = 0.343$, *p-value* $<$ 0.001) and of BTRAN ($\beta = 0.385$, *p-value* $<$ 0.001) on SCPERF.

5.4. Multigroup comparison: measurement model invariance

Cross-culture measurement invariance of the constructs in our model has been tested by comparing the fit of nested models including an increasing level of invariance. We used the Robust Chi-Square Difference Test (Satorra and Bentler, 1994), and the difference in Robust Comparative Fit Indexes (ΔCFIs) (Chen, 2007; Cheung and Rensvold, 2002) for comparting the fit of nested models. We consider two models to fit the same if ΔCFI <0.01 (Chen, 2007) and the *p-value* associated

Table 4
Reliability results (pooled results).

Construct	Cronbach's Alpha [C. I.][a]	Composite Reliability[b]	Average Variance Extracted
KNSH	0.882 [0.862; 0.902]	0.883	0.653
TPPS	0.880 [0.860; 0.900]	0.882	0.715
BADOP	0.869 [0.846; 0.892]	0.870	0.690
BTRAN	0.886 [0.867; 0.905]	0.886	0.660
SCTRAN	0.899 [0.883; 0.914]	0.899	0.640
SCPERF	0.944 [0.935; 0.952]	0.944	0.628

[a] Values in bracket are the bounds of a 95% Confidence Interval computed according to Trinchera et al. (2018).
[b] Coefficient (Raykov, 2001).

Table 5
Correlation among the constructs (pooled results): italic values on the diagonal represent square roots of the AVE values reported in Table 4.

CONSTRUCT	KNSH	TPPS	BADOP	BTRAN	SCTRAN	SCPERF
KNSH	*0.808*					
TPPS	0.852	*0.846*				
BADOP	0.922	0.889	*0.831*			
BTRAN	0.786	0.759	0.853	*0.812*		
SCTRAN	0.744	0.718	0.807	0.689	*0.800*	
SCPERF	0.794	0.766	0.862	0.839	0.816	*0.792*

Table 6
Discriminant Validity - HTMT approach (pooled results).

CONSTRUCT	KNSH	TPPS	BADOP	BTRAN	SCTRAN	SCPERF
KNSH	1					
TPPS	0.859	1				
BADOP	0.883	0.845	1			
BTRAN	0.793	0.808	0.775	1		
SCTRAN	0.744	0.733	0.743	0.780	1	
SCPERF	0.807	0.775	0.801	0.859	0.836	1

Table 7
Path coefficients (pooled results).

Hypotheses	Path	Beta	s.e.	t-statistics	p-values	Decision
H1	KNSH– > BADOP	0.576	0.062	9.306	<0.001	Accepted
H2	TPPS– > BADOP	0.342	0.058	5.896	<0.001	Accepted
H3a	BADOP– > SCTRAN	0.798	0.048	16.75	<0.001	Accepted
H3b	BADOP– > BTRAN	0.832	0.049	17.081	<0.001	Accepted
H4	BADOP– > SCPERF	0.253	0.092	2.757	0.006	Accepted
H5	SCTRAN– > SCPERF	0.343	0.056	6.116	<0.001	Accepted
H6	BTRAN– > SCPERF	0.385	0.08	4.793	<0.001	Accepted

with the Robust Chi-Square Difference Test is < 0.05. Between two equivalent models, the less complex (i.e. one (with a higher degree of freedom)) is preferred.

In the first step, we tested our data for the configural invariance between the Indian and the US respondents. The configural invariance model (Model 1: configural invariance in Table 8) assumes the same structure in the loading matrix (i.e. items are associated with the same latent constructs in the two sub-samples), but different values for the loadings in the two sub-samples. After verification of configural invariance, we tested for metric invariance. The metric invariance model (Model 2: weak invariance in Table 8) constrains the loadings to be the same between the two sub-samples. Successively, we tested for the scalar invariance (Model 3: strong invariance in Table 8) by constraining both the loadings and the intercepts to be the same between the two sub-samples. To conclude, we tested for strict and scalar invariances. The strict invariance model (Model 4: strict invariance in Table 8) imposes the loadings, the intercepts and the residual variances to be equal between the two sub-populations. The strong, scalar invariance model (Model 5: scalar invariance in Table 8) constrains the loadings, the intercepts, the residuals variances and the latent variable means to be equal.

The series of model comparisons in Table 8 indicates that strict invariance is verified for the measurement model across the Indian and the US samples. Strong scalar invariance is rejected when considering the *p-value* associated to the Robust Chi-Square Difference Tests, while it is verified when referring to the ΔCFI. According to these results, we assume the factor loadings, the intercepts, and the residual variances to be equal between Indian and US samples.

5.5. Multigroup comparison: structural model invariance

Results in Table 8 supports measurement invariance between the Indian and the US samples. We can now compare the two sub-samples in terms of structural model parameters. To test for structural invariance, we fit a series of the model each constraining a structural path separately (Chin et al., 2016). We then compare the fit of these models to a baseline model that assumes measurement invariance and unconstrained path coefficients between the two sub-samples. As for the measurement invariance, we consider a constrained model to equally fits the data compared to the baseline model if the ΔCFI <0.01 (Chen, 2007) and the *p-value* associated to the Robust Chi-Square Difference Test is < 0.05. If the constrained and the baseline models fit the same, we conclude that there is no significant difference in the constrained path coefficient between the two sub-samples. We report, in Table 9, the path coefficients at a country level along with their significance level and the Robust Chi-Square Difference Tests results when comparing the baseline model to the model imposing the corresponding path to be equal between the sub-sample.

Results show no significant differences when comparing Indian and US respondents path coefficients, though the relation between BADOP and SCPERF is not significant at $p < 0.05$ for the US sample. Multigroup comparison support the idea that the measurement model is the same for both the Indian and US respondents and that there is no difference in the structural model.

5.6. Moderation effect of the respondents' background industry

To investigate the moderation effect of the background industry of the respondents on the relations that are created in the model, we performed a multigroup analysis by comparing the respondents from

Table 8
Tests for measurement invariance between Indian and US samples.

Model	SB $\chi2$	df	Robust CFI	Robust RMSEA	Model Comparison	Δ $\chi2$[a]	*p-value*	Δ CFI
Baseline model, India	441.737	369	0.976	0.033	- - - - - - - - -	- - - - - - -	- - - - - -	- - - - - -
Baseline model, US	450.102	369	0.985	0.032	- - - - - - - - -	- - - - - - -	- - - - - -	- - - - - -
Model 1	891.765	738	0.983	0.024	- - - - - - - - -	- - - - - - -	- - - - - -	- - - - - -
Model 2	914.020	761	0.983	0.023	2 vs. 1	20.588	0.606	0.000
Model 3	938.320	784	0.983	0.023	3 vs. 2	20.897	0.587	0.000
Model 4	957.905	813	0.984	0.022	4 vs. 3	19.927	0.895	0.001
Model 5	984.332	819	0.981	0.023	5 vs. 4	66.157	<0.001	0.002

Model 1, model for configural invariance – no constrains; Model 2, model for weak invariance – same loadings; Model 3, model for strong invariance – same loading and intercepts; Model 4, model for strict invariance – same loading, intercepts and residual variances; Model 5, model for scalar invariance – same loadings, intercepts, residual variances and latent variable means.

[a] Scaled Chi Square Difference as defined by Satorra and Bentler (1994).

Table 9
Path Coefficients: comparison between US and India assuming measurement invariance.

Hypotheses	Path	Beta India	Beta US	Δ χ2[a]	p-values	Significant Difference[b]
H1	KNSH– > BADOP	0.602***	0.579***	0.027	0.874	No
H2	TPPS– > BADOP	0.248*	0.377***	0.716	0.397	No
H3a	BADOP– > SCTRAN	0.794***	0.797***	0.001	0.973	No
H3b	BADOP– > BTRAN	0.831***	0.831***	0.000	0.991	No
H4	BADOP– > SCPERF	0.345***	0.200[NS]	0.749	0.387	No
H5	SCTRAN– > SCPERF	0.221**	0.430***	2.213	0.137	No
H6	BTRAN– > SCPERF	0.398***	0.366***	0.043	0.836	No

Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
[a] Scaled Chi Square Difference as defined by Satorra and Bentler (1994).
[b] At p-value ≤ 0.001.

manufacturing industry to respondents from all the other industries. We followed the same procedure as described in sub-sections 5.4 and 5.5, and then we used the same thresholds to judge the equivalence of the measurement and structural models between the manufacturing and non-manufacturing industries.

By comparing the fit of the different nested models in Table 10, we verified the measurement model invariance at the configural, metric and scalar levels (no significant difference with respect to the Robust Chi-Square Difference, and ΔCFI < 0.01 for the three nested comparisons). We can therefore conclude on the stability of the measurement model between respondents from a manufacturing industry versus respondents from a non-manufacturing industry: the intercepts and the loadings are the same across the two groups.

Following the verification of the measurement invariance among respondents from different industries, we tested for the moderation effect of the background industries of the respondents on each relation in the structural model. We thus compared the fit of a series of models, with each constraining a structural path separately to a baseline model that assumes measurement invariance and unconstrained path coefficients among industries. Results in Table 11 show no significant differences when comparing respondents from a manufacturing industry to those in a non-manufacturing industry. According to our results, there is no evidence for an effect of the industry background of the respondents on the results.

6. Discussion and implications

The purpose of this paper is to examine the relationship between blockchain and supply chain performance. This study contributes to enriching the extant literature on logistics, supply chain management, and blockchain technologies, as it helps to unlock and enhance our understanding of supply chain performance and the impact of blockchain. Our findings offer significant insights from the managerial and theoretical perspectives, providing valuable input to help tackle contemporary challenges in the area of logistics and supply chain management (Goldsby and Zinn, 2016; Zinn and Goldsby, 2017a, 2017b), as well as emerging opportunities in the digital age.

In line with the previous literature on technology adoption, the results obtained from the verification of our hypotheses showed that these were confirmed, then bringing essential insights and validating new constructs for the integration of blockchain into the supply chain environment. For instance, the constructs Knowledge sharing (H1) and Trading Partner Pressure (H2) are being found to impact blockchain adoption in both countries, India and the US. The validation of these two constructs applied to the integration of blockchain with supply chain is fundamental: while these two constructs have been already investigated, they were not concerned with the issue of blockchain. For instance, Lin (2017) found a significant positive effect of knowledge sharing diffusion in electronic supply chain management, but there was not any relationship with blockchain. Moreover, our results about trading partner pressure were in line with previous literature on technology adoption (Low et al., 2011; Wang et al., 2010), but without anything related to blockchain.

Our proposed hypotheses H3a and H3b were dealing with the effect of blockchain adoption on supply chain transparency and blockchain transparency, respectively. Not surprisingly, the results confirmed previous studies: the power of blockchain to enable more transparency in supply chains (Thakur et al., 2019; Kshetri, 2018; Lu and Xu, 2017) is real and verifiable. By contrast, previous studies on blockchain adoption (Kamble et al., 2018; Francisco and Swanson, 2018) could not demonstrate the impact of blockchain adoption, supply chain transparency and blockchain transparency on supply chain performance as postulated in hypotheses H4, H5 and H6, respectively. Our findings validated these relationships and actually contributed to enriching the blockchain literature (Thakur et al., 2019; Aste et al., 2017; Kshetri, 2018; Zou et al., 2018).

It is worthwhile indicating that our results reinforce previous literature conclusions on the challenges and the benefits of blockchain in

Table 10
Tests for measurement invariance at the industry level.

Model	SB χ2	df	Robust CFI	Robust RMSEA	Model Comparison	Δ χ2[a]	*p-value*	Δ CFI
Baseline model, Manufacturing	455.396	369	0.958	0.036	- - - - - - - - -	- - - - - - -	- - - - - -	- - - - - -
Baseline model, Non-manufacturing	511.014	369	0.979	0.026	- - - - - - - - -	- - - - - - -	- - - - - -	- - - - - -
Model 1	968.684	738	0.976	0.029	- - - - - - - - -	- - - - - - -	- - - - - -	- - - - - -
Model 2	992.057	761	0.976	0.029	2 vs. 1	31.653	0.108	0.000
Model 3	1020.613	784	0.975	0.029	3 vs. 2	21.823	0.531	0.001
Model 4	1172.798	813	0.963	0.035	4 vs. 3	62.971	<0.001	0.013
Model 5	1191.432	819	0.961	0.035	5 vs. 4	22.927	0.001	0.001

Model 1, model for configural invariance – no constrains; Model 2, model for weak invariance – same loadings; Model 3, model for strong invariance – same loading and intercepts; Model 4, model for strict invariance – same loading, intercepts and residual variances; Model 5, model for scalar invariance – same loadings, intercepts, residual variances and latent variable means.
[a] Scaled Chi Square Difference as defined by Satorra and Bentler (1994)

Table 11
Path Coefficients comparison between manufacturing and non-manufacturing industries.

Hypotheses	Path	Beta Manufacturing	Beta Non-manufacturing	Δ χ2[a]	p-values	Significant Difference[b]
H1	KNSH– > BADOP	0.682*	0.559***	0.176	0.674	No
H2	TPPS– > BADOP	0.245 [NS]	0.363***	0.178	0.673	No
H3a	BADOP– > SCTRAN	0.699***	0.808***	1.109	0.292	No
H3b	BADOP– > BTRAN	0.738***	0.846***	2.596	0.107	No
H4	BADOP– > SCPERF	0.395***	0.183[NS]	1.687	0.194	No
H5	SCTRAN– > SCPERF	0.340***	0.353***	0.019	0.890	No
H6	BTRAN– > SCPERF	0.253***	0.446***	2.101	0.147	No

Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
[a] Scaled Chi Square Difference as defined by Satorra and Bentler (1994).
[b] At p-value ≤ 0.001.

supply chains (Schmidt and Wagner, 2019). It means that our findings are in line with the main findings of other authors, one of them being that blockchain could enable more transparency in transactions and contribute to minimizing transaction costs. Moreover, our findings on supply chain transparency, blockchain transparency and supply chain performance suggest that the various weaknesses reported by Babich and Hilary (2020), including the lack of privacy and standardization, and inefficiency, could have different perceptions in supply chains. Therefore, it is important to note that all hypotheses were supported in both the Indian and American contexts (see Table 9), that is, our results suggest that there are no significant differences between the path coefficients of Indian and US respondents. If we consider that fact that single countries have so far been the focus of researchers (Wong et al., 2019; Kamble et al., 2018), it clearly appears that our findings should have important implications. These are discussed in the next section.

6.1. Managerial implications

By shedding more light on the relationship between blockchain and supply chain performance, this study should certainly help managers to better grasp this important aspect of an issue that needs their informed decision. More specifically, the results of the study show strong evidence about decision-makers' behavior in relation to the relationship between blockchain and supply chain performance in two countries (India and the US). The extant logistics and supply chain literature (Autry et al., 2014; Grawe et al., 2011) has highlighted the importance of supply chain performance in all contemporary businesses, as well as the need for managing effectively the supply chain integration (Turkulainen et al., 2017). In this outlook, our research opens up an avenue by developing and testing a model that establishes strong relationships between blockchain and supply chain performance.

The findings unveil essential challenges facing managers. In the first place, managers have to gain an in-depth understanding of the blockchain adoption complexities. As indicated by the results of this study, knowledge sharing (KNSH) and trading partner pressure (TPPS) exert substantial influence on blockchain adoption in both countries, India and the US. However, managers are challenged to detect countries' particularities in some cases. Managers of firms operating in a global market must, therefore, adjust their marketing policies and decisions bearing in mind the existence of differences in blockchain adoption behavior across the countries. In line with prior studies reporting knowledge development in supply chains (Grawe et al., 2015, 2011; Schoenherr et al., 2014; Waller and Fawcett, 2014), our results confirm that knowledge is a critical resource in blockchain and supply chain integration for increased performance.

To effectively support the development of blockchain in the supply chain field, managers should put in the effort to better grasp the relationship between blockchain adoption and supply chain performance. Our results showed that supply chain transparency and blockchain transparency nurture a strong direct relationship. In practice, managers should be aware that blockchain is a strong predictor of supply chain performance. Therefore, they are expected to improve their understanding of blockchain transparency and supply chain transparency. For example, the extant literature on blockchain reports that many improvements are being noticed for aspects such as transparency, visibility and accountability in supply chains owing to blockchain applications (Aste et al., 2017; Biswas et al., 2017; Kshetri, 2018). If firms' managers upgrade their understanding of the relationship between blockchain and supply chain performance, they will potentially play a more fundamental role in supporting their various organizations' operations.

6.2. Theoretical implications, limitations and future research

From a theoretical perspective, this study firstly contributes to shedding more light on the disruptions, complexities and dynamics in logistics and supply chains imposed by the emerging technologies. Secondly, this study kick-starts a research stream about blockchain and supply chain performance, with a robust theoretical model. The results validated the model in two countries, India and the US. Our results answered the two research questions, showing that blockchain is an effective technology to support supply chain performance. Regarding the second question, our results found no significant differences between countries, concerning blockchain adoption and supply chain performance in an integrated conceptual model; however, more empirical research is required to confirm this behavior.

Thirdly, the study's results revealed that blockchain adoption has a high positive influence on supply chain performance and that the supply chain performance is significantly influenced by supply chain transparency and blockchain transparency. From a theoretical lens, this reinforces the idea that supply chain performance can be predicted by a set of constructs. Lastly, the findings show that, despite the embryonic development of blockchain, its influence on supply chain operations cannot be neglected, and should, on the contrary, be more empirically investigated with a view to a better understanding.

As for the main limitations of this study, we believe that adding variables (Golicic et al., 2012) to predict the direct and mediated effects of blockchain adoption and supply chain transparency/blockchain transparency on supply chain performance, can enrich the model. Such variables include accountability (Zou et al., 2018), confidence in the process, and the effect of data sharing (Lu and Xu, 2017), all of this in a blockchain context. Integrating these variables in order to adapt and expand our model may be an interesting topic for future studies. So goes with the examination of the negative outcomes (Gligor, 2014) of the relationship between blockchain and supply chain performance, although our research rather concluded with positive results in this regard. On the other hand, since the literature related to technology adoption (Dwivedi et al., 2017b, 2017a; Behnke and Janssen, 2019; Kamble et al., 2019) has not yet proposed a model similar to the one developed in this study, it may useful to compare our findings with others. However, this limitation does not affect the contribution of this work.

As a reminder, the respondents from the manufacturing industry are being compared with their counterparts from all the other industries. According to our results, there is no evidence attesting a moderation effect of the (binary) industry variable on the results. However, it should be noted that our sample composition could not enable us to compare respondents from several types of industry from an intersectoral perspective. This analysis could have been an interesting approach for future studies to deeply investigate the link between blockchain and supply chain performance.

Moreover, while our model and results represent a strong contribution to the advancement of the literature on the integration of blockchain with supply chains, there is an urgent need to carry out more research in this area. Our model considers two constructs to predict blockchain adoption (knowledge sharing, and trading partner pressure), and further research may usher in other enriching developments. For instance, reciprocal connectivity (Autry et al., 2014), logistics innovation (Grawe et al., 2015) and other knowledge predictors (Schoenherr et al., 2014) may come in, but also operational flexibility (Gligor, 2014). Moreover, key aspects such as blockchain transparency (Jeppsson and Olsson, 2017), the impact of the blockchain on supply chain security (Kshetri, 2017b) and on performance need further investigation.

Another limitation of this study lies in the fact that the impact of the smart contract (Kim and Laskowski, 2017; Lu and Xu, 2017) on the supply chain performance was not explored. Future studies can address this gap, by adapting our model. Finally, our model was tested in one developed country and one emerging economy, but our study's findings can be generalized only of more empirical investigations across the world are conducted. Thus, we encourage the logistics and supply chain community to continue to investigate the relationship between blockchain and supply chain performance.

7. Conclusion

The primary objective of this study was to show strong empirical evidence of the relationship between blockchain and supply chain performance in two selected countries, with the hope that the results obtained may serve as a catalyst for further research and be generalized. Our proposed research model was strongly supported by the results obtained. In fact, they indicated that knowledge sharing and trading partner pressure are good predictors of blockchain adoption in the Indian and US contexts. Additionally, our results highlighted the importance of supply chain transparency and blockchain transparency, both of which are important antecedents of supply chain performance. These results are in line with theory, which highlighted the benefits of blockchain in supply chains, including an improvement of performance (Wang et al., 2019; Kamble et al., 2019).

These results have potential managerial and theoretical implications. From a managerial lens, our model showed the value and influence of all constructs on supply chain performance, as well as the impact of the relationship between blockchain adoption and supply chain performance on firm's competitiveness. It further suggests to managers to deploy more efforts to enhance their understanding of this relationship. In terms of theoretical approach, we showed to the logistics and supply chain management community the strong relationship existing between blockchain and supply chain performance, the needs for a more impactful role, and robust empirical studies that can help tackle the new challenges of the digital age. Thus, we opened up a new research avenue for scholars and practitioners interested in improving the understanding of the relationship between blockchain and supply chain performance in other areas and contexts. Finally, by comparing respondents from the manufacturing industry to respondents from other industries, we found no evidence for a moderation effect of the industry variable on the results. Moreover, our sample composition could not allow us compare respondents from a greater number of industry types from an intersectoral perspective. This analysis could instigate future studies to further the investigation of the link between blockchain and supply chain performance. Investigating also the particularities of other countries through industry respondents seems to be another important research direction.

Author contribution

Author	Contribution
Samuel Fosso Wamba	• Idea generation and formulation • Research goals and aims • Theory building: selection of relevant theories • Creation of the research model • Guide for literature review • Survey design and pilot testing • Management and coordination of the final data collection by a market research firm • Secure funding for the data collection • Co-writing of the first draft, advanced draft, and final paper • Conduct the initial data analysis and interpretation • Finalize the paper • Participate in the whole revision process of the manuscript • Coordinate the team during the entire process
Maciel M. Queiroz	• Lead the writing of the first draft • Co-writing of the conception and design • Co-writing of the advanced draft and final paper • Lead and conduct the literature review • Validation of the selected theories • Development and design of methodology • Validation of the final survey • Critically revising the article for relevant intellectual content • Participate in the whole revision process of the manuscript • Co- coordination responsibility for the research activity planning and execution
Laura Trinchera	• Lead the data analysis • Be responsible for the data curation and formal analysis • Implementation of the computer code and supporting algorithms • Conduct all complex data analysis and interpretation • Preparation, creation, presentation and statistical interpretation of the data analysis results • Co-writing of the advanced draft and final paper (methods and results) • Conduct all additional analysis required during the review process as well as interpretation • Participate in the whole revision process of the manuscript

Appendix A. Scale items

Construct	Label	Measures	Adapted from
BADOP	BADOP1	My company invests resources in blockchain-enabled supply chain applications.	(Martins, Oliveira, and Thomas (2016) and (Kim and Garrison (2010)
	BADOP2	Business activities in our company require the use of blockchain technologies.	
	BADOP3	Functional areas in my company require the use of blockchain technologies.	
BTRAN	BTRAN1	I believe blockchain enabled-supply chain processes would be transparent.	(Venkatesh et al., 2016; Awaysheh and Klassen (2010); Morgan et al., 2018)
	BTRAN2	I believe supply chain stakeholders will enable me to have a better understanding of how blockchain-enabled supply chain applications work.	
	BTRAN3	I believe supply chain stakeholders will provide me with in-depth knowledge of blockchain applications in the supply chain.	
	BTRAN4	I believe I will have opportunities to provide feedback on blockchain-enabled supply chain applications.	
KNSH	KNSH1	Your firm prefers to share know-how, innovations and blockchain-enabled supply chain knowledge with supply chain partners.	(H.-F. Lin, 2017)
	KNSH2	Your firm prefers to share relevant market knowledge and blockchain-enabled supply chain knowledge with supply chain partners.	
	KNSH3	Your firm openly shares knowledge on blockchain-enabled supply chain applications with your supply chain partners.	
	KNSH4	Your firm and supply chain partners share knowledge on blockchain-enabled supply chain applications that help in the establishment of business planning.	
SCPERF	SCPERF1	Our supply chain is able to handle nonstandard orders.	Qrunfleh and Tarafdar (2014)
	SCPERF2	Our supply chain is able to meet special customer specification requirements.	
	SCPERF3	Our supply chain is able to produce products characterized by numerous features options, sizes and colors.	
	SCPERF4	Our supply chain is able to rapidly adjust capacity so as to accelerate or decelerate production in response to changes in customer demand.	
	SCPERF5	Our supply chain is able to rapidly introduce large numbers of product improvements/variations.	
	SCPERF6	Our supply chain is able to handle rapid introduction of new products.	
	SCPERF7	Our supply chain has a fast customer response time.	
	SCPERF8	Our supply chain is characterized by a great amount of cross-over of the activities of our firm and our trading partners.	
	SCPERF9	Our supply chain is characterized by a high level of integration of information systems in our firm.	
	SCPERF10	Our supply chain has a short order-to-delivery cycle time.	
SCTRAN	SCTRAN1	Consider to what extend blockchain could improve the following tasks: recording and transferring quantities of assets (e.g., pallets, trailers, containers), as they move between supply chain nodes.	(Vorabutra, 2016)
	SCTRAN2	Consider to what extent blockchain could improve the following tasks: tracking purchase orders, change orders, receipts, shipment notifications, or other trade-related documents.	
	SCTRAN3	Consider to what extend blockchain could improve the following tasks: assigning or verifying certifications or certain properties of physical products; for example, determining if a food product is organic or fair-trade.	
	SCTRAN4	Consider to what extend blockchain could improve the following tasks … linking physical goods to serial numbers, bar codes, digital tags (e.g., RFID)	
	SCTRAN5	Consider to what extend blockchain could improve the following tasks: sharing information about manufacturing process, assembly, delivery, and maintenance of products with suppliers and vendors.	
TPPS	TPPS1	The major trading partners of my company encouraged the implementation of blockchain technologies.	Wang et al. (2010)
	TPPS2	The major trading partners of my company recommended the implementation of blockchain technologies.	
	TPPS3	The major trading partners of my company requested the implementation of blockchain technologies.	

Appendix B. Some examples demonstrating the performance claim of blockchain

#	Example	Brief Description	Source
1	Maersk and IBM Introduce TradeLens Blockchain Shipping Solution	A platform based on blockchains is being built to promote the efficiency of shipping operations involving ports, terminals, customs authorities, freight forwarders, and importers/exporters, etc. The project was successfully tested for a period of 12 months, and it demonstrated benefits such as increased efficiency, performance, transparency and collaboration. For instance, the transit time for shipping packing materials dropped by 40% in the USA owing to blockchain-based platforms.	https://www.maersk.com/news/2018/06/29/maersk-and-ibm-introduce-tradelens-blockchain-shipping-solution
2	Case Study: How Walmart brought unprecedented transparency to the food supply chain with Hyperledger Fabric	In this case, Walmart applied a blockchain traceability systems, supported by Hyperledger in the food supply chain. The blockchain application enabled the company to trace easily over 25 products from different suppliers, thus improving supply chain performance.	https://www.hyperledger.org/resources/publications/walmart-case-study
3	Delloite, 2019 Global Blockchain Survey - Blockchain gets down to business	In this survey, Deloitte questioned senior executives worldwide about their attitudes toward blockchain investments. One interesting point was that 86% of the participants agreed about the power of blockchain in supporting new business and revenue streams. Also, the survey showed that 77% of the executives recognize that not adopting blockchain would make their companies lose competitive advantage. (N = 1386 companies)	https://www2.deloitte.com/content/dam/Deloitte/se/Documents/risk/DI_2019-global-blockchain-survey.pdf

Appendix C. Loading factor (pooled results)

Construct	Item	Loading	se	p-value	ci.lower	ci.upper
KNSH	KNSH1	1				
	KNSH2	0.911	0.034	26.708	0.844	0.978
	KNSH3	0.926	0.037	24.828	0.853	0.999
	KNSH4	0.924	0.038	24.074	0.849	0.999
TPPS	TPPS1	1				
	TPPS2	0.975	0.030	32.394	0.916	1.034
	TPPS3	0.894	0.034	25.983	0.826	0.961
BADOP	BADOP1	0.991	0.043	23.208	0.907	1.075
	BADOP2	0.947	0.034	28.023	0.880	1.013
	BADOP3	1				
BTRAN	BTRAN1	0.978	0.054	18.154	0.872	1.084
	BTRAN2	0.982	0.047	20.924	0.890	1.074
	BTRAN3	0.977	0.047	20.686	0.884	1.070
	BTRAN4	1				
SCTRAN	SCTRAN1	1				
	SCTRAN2	0.947	0.034	27.622	0.880	1.014
	SCTRAN3	0.954	0.037	25.685	0.881	1.027
	SCTRAN4	0.936	0.037	25.195	0.863	1.009
	SCTRAN5	0.970	0.037	26.312	0.898	1.042
SCPERF	SCPERF1	0.897	0.037	23.919	0.823	0.970
	SCPERF2	0.891	0.035	25.178	0.821	0.960
	SCPERF3	1				
	SCPERF4	0.976	0.031	31.922	0.916	1.036
	SCPERF5	0.990	0.039	25.105	0.912	1.067
	SCPERF6	0.994	0.041	24.006	0.913	1.075
	SCPERF7	0.930	0.041	22.684	0.849	1.010
	SCPERF8	0.913	0.040	23.069	0.836	0.991
	SCPERF9	0.857	0.040	21.247	0.778	0.936
	SCPERF10	0.919	0.036	25.613	0.848	0.989

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