International Journal of Information Management 46 (2019) 70–82

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA

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ARTICLE INFO

Keywords:
Blockchain
Adoption
Supply chain network
Digital disruption
UTAUT

ABSTRACT

The digitalization phenomenon is leveraging new relationship models through the entire supply chain network. In this outlook, blockchain is a cutting-edge technology that is already transforming and remodeling the relationships between all members of logistics and supply chain systems. Yet, while studies on blockchain have gained a relative pace over the recent years, the literature on this topic does not report sufficient research cases on blockchain adoption behavior at the individual level. The present study, therefore, aims to bridge this gap, notably by helping understand the individual blockchain adoption behavior in the logistics and supply chain field in India and the USA. Drawing on the emerging literature on blockchain, supply chain and network theory, as well as on technology acceptance models (TAMs), we have developed a model based on a slightly-altered version of the classical unified theory of acceptance and use of technology (UTAUT). The model being developed was then estimated using the Partial least squares structural equation modeling (PLS-SEM). As the model was eventually supported, the results obtained revealed the existence of distinct adoption behaviors between India-based and USA-based professionals. In parallel, the findings appear as a useful contribution to and a sign of progress for the literature on IT adoption, SCM, and blockchain.

1. Introduction

Over the recent years, to the exponential growth of information and communication technologies (ICTs) has given rise to several disruptions in all business models, mainly in the logistics and supply chain management (L/SCM) field (Goldsby & Zinn, 2016). Because of these disruptions, L/SCMs have been experimenting several effects while putting in substantial efforts to reconfigure their operation models (Büyüközkan & Göçer, 2018). Thus, the relationships and operations models can increase substantially their complexities with this new ingredient. This relates for instance to trust between supply chain members, transparency, and accountability through the network (Morgan, Richey, & Ellinger, 2018), collaboration (Tsanos & Zografos, 2016), knowledge sharing (Wagner & Buko, 2005), and demand and supply chain integration (Stolze, Murfield, & Esper, 2015), among others. However, cutting-edge technologies are emerging, with a high potential to improve the SCM operations models and to disrupt inefficient models.

In this context, one of the most prominent technologies is blockchain (Aste, Tasca, & Di Matteo, 2017; Y. Chen, 2018; Kshetri, 2018; Viryasitavat, Da Xu, Bi, & Sapsomboon, 2018). Even though the application of blockchain technologies in the L/SCM context is still at its initial stages, this does not repel the fact that this technology will surely remodel the L/SCM relationships (Biswas, Muthukkumarasamy, & Tan, 2017; Kshetri, 2018; Lu & Xu, 2017), together with the consumption behavior of the society (Aste et al., 2017). For some time now, blockchain technology is being employed in a wide array of contexts, ranging from open manufacturing (Li et al., 2018) and real state—to ensure fraud prevention (Veuger, 2018)—to clinical trials (Benchoufi, Porcher, & Ravaud, 2017) and entrepreneurship innovation (Y. Chen, 2018), amongst others.

Supply chain managers should adopt blockchain for their operations because virtually all transactions with blockchain are safer, more transparent, traceable and efficient (Aste et al., 2017; Kshetri, 2018). In addition, the cooperation between supply chain members tends to increase (Aste et al., 2017), reflecting on costs reduction and increased efficiency in the supply chain. Furthermore, the blockchain adoption can enhance customers' trust, which will allow them to check the entire journey of goods across the supply chain in full confidence. In this regard, the traceability (Biswas et al., 2017) mechanisms of the blockchain will support products fraud prevention and fake across the supply chains (R. Chen, 2018). As result, supply chains will gain a lot in terms

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https://doi.org/10.1016/j.ijinfomgt.2018.11.021
Received 15 September 2018; Received in revised form 30 November 2018; Accepted 30 November 2018

of costs reductions and efficiency.

The emerging literature on blockchain has reported various benefits and advantages of this technology that can directly impact the L/SCM. They include transparency and accountability (Kshetri, 2018; Zou et al., 2018), traceability and fraud prevention (Biswas et al., 2017; R. Chen, 2018; Lu & Xu, 2017), cybersecurity and protection (Kshetri, 2017), etc. The blockchain technology can rely on its tamper-proof characteristic (Aste et al., 2017; Viryasitavat et al., 2018) to remodel relationship paradigms between all members of the supply chain. As blockchain applied to L/SCM is still at its infancy stage, most of the organizations are yet to go beyond analyses leading to the adoption phase. This is why, as indicated by the literature on technology acceptance models (TAMs) (Davis, 1989; Venkatesh, Thong, & Xu, 2012; Venkatesh, Morris, Davis, & Davis, 2003), various authors have dedicated significant efforts to help understand how individuals behave when it comes to accepting to use a technology.

In this vein, the unified theory of acceptance and use of technology (UTAUT) of previous TAM (Venkatesh et al., 2003), whose extension is UTAUT2 (Venkatesh et al., 2012), is a suitable approach to gain understanding of the blockchain adoption in the supply chain field. The UTAUT is a robust model in which the variance explained by behavioral intention achieved 56%, and technology use, 40%. However, the UTAUT2 outperforms these results, reaching 74% and 52%, respectively for behavioral intention and technology use (Venkatesh et al., 2012).

A good number of recent studies have integrated technology acceptance models in various contexts (Fosso Wamba, Bhattacharya, Trinchera, & Ngai, 2017; Huang, Liu, & Chang, 2012; Liébana-Cabanillas, Marinković, & Kalinić, 2017; Lin, 2011; Mamonov & Benbunan-Fich, 2017; Mortenson & Vidgen, 2016; Wu, Zhao, Zhu, Tan, & Zheng, 2011; Zhang, Weng, & Zhu, 2018). In addition, few empirical studies using surveys on blockchain and supply chain were reported in the literature (Fosso Wamba, Kamdjoug, Robert, Bawack, & Keogh, 2018; Kamble, Gunasekaran, & Arha, 2018).

However, the blockchain adoption behavior and the drivers for such adoption in organizations remain scarcely investigated, according to the extent relevant literature. Therefore, we aim to answer the following research question (RQ) to shed more light on the employees' behaviors associated with blockchain adoption: *what are the drivers of blockchain adoption in the supply chain*?

Moreover, this study aims to provide the supply chain and logistics community with the finest discussion elements for a better understanding of the current impact of the blockchain technology on the adoption behavior of professionals (individual level). The study further seeks to spur supply chain stakeholders to rethink their internal relationships in order to keep abreast of this digital age where blockchain is quickly gaining ground. To answer our research question, this study draws on the recent literature on blockchain (Aste et al., 2017; Banerjee, Lee, & Choo, 2018; Francisco & Swanson, 2018; Kano & Nakajima, 2018; Kshetri, 2018), network theory (Borgatti & LI, 2009; Burt, 1980; Grandori & Soda, 1995; Granovetter, 1973), considering that the L/SCM is a complex network and that a better understanding supply chain relationships and networks evolution requires the latest available information. As the primary objective of this study is related to the blockchain adoption, our theoretical model was based also on the literature on technology acceptance models (2012, Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Yi, Jackson, Park, & Probst, 2006).

This paper contributes to enriching the literature on IT adoption, as it reports blockchain adoption as a hot topic for scholars and practitioners, who are eager to gain an in-depth understanding of the adoption behavior at the individual level. Additionally, this study contributes to the advancement of the logistics and SCM field, because it unveils the blockchain implications for SCM. As for the remainder of this paper, Section 2 describes the fundamental concepts and perspectives for blockchain, supply chain and related networks, but also the various applicable technology acceptance model theories. In Section 3, we derive our research model, followed by a description of the selected methodology and the main results in Section 4. Section 5 deals with the discussion of such results, the implications for research and practice, as well as the limitations of the research coupled with some suggestions for future research. Finally, Section 6 exhibit the main conclusions of this study.

2. Theoretical background

2.1. Blockchain applications: fundamentals

Blockchain emerged in the cryptocurrency market as a disrupting technology (Nakamoto, 2008). The blockchain core is related to a distributed database (ledgers) (Kano & Nakajima, 2018) that performs in a shared and synchronized environment (chain), in which information is validated by the users (Aste et al., 2017). This implies a decentralized system where the validation of transactions does not give rise to any alteration (Y. Chen, 2018) and where the tamper-proof characteristic of blockchain constantly comes into play. Moreover, all transactions can be traceable, and consequently, organizations can achieve the genesis node. In essence, the data are organized into blocks that shape a chain (Li et al., 2018), and the current block is expected to store the information of the previous block. Fig. 1 synthesizes the blockchain fundamentals.

Source: Adapted from (Manhart, 2017)

Blockchain transactions operate in a peer-to-peer network, in a decentralized way (Y. Chen, 2018). In other words, the transactions are validated and stored by a distributed consensus, and it is not necessary to have a central entity that validates the transactions. The Fig. 1 shows that each block is connected (chain) with the preceding one, and that this integration makes it easier to any information history to be recovered only by exploring the previous blocks. Each block has its own hash, with a unique ID, and it also brings the hash of the previous block and generates more transaction security. In addition, the blocks store a set of transactions that are recorded and validated by other computers of the same network. In this process, the transactions receive a unique sequence and time (timestamp). Once the transaction is validated, it cannot be modified. Furthermore, transparency of the operations is strengthened because the transactions are shared across the network, together with any useful information, thereby enabling all network actors to informed of all in due time. At the same time, this triggers trust. As indicated, blockchain integrated with the supply chain field has the potential to transform the relationship between network members increase efficiency and streamline transactions costs.

Considering the supply chain context, there is a clear implication with related traditional constructs such as trust between the participants, cooperation, knowledge, information exchange, etc. Recent studies have been investigating the impact of blockchain in supply chains. Focus has been on elements such as cost, quality, risk reduction, and flexibility (Kshetri, 2018), product traceability problems (Biswas et al., 2017; R. Chen, 2018; Lu & Xu, 2017), and anti-counterfeits (Toyoda, Mathiopoulos, Sasase, & Ohtsuki, 2017). Almost all organizations want to take advantage of the great deal of improvments brought about by blockchain, which span enhanced process and operations through the entire supply chain, safer, transparent and efficient transactions (Kshetri, 2018), and trust and reliability across the network, all transactions and related information being shared by all network participants. Therefore, the relationships between stakeholders (cooperation and trust, among others) will be very positively affected in supply chains. Moreover, products traceability can be improved significantly (Biswas et al., 2017), allowing customers to check the entire journey of a particular product and upgrading the level of logistics service. All of this adds to a significant streamlining of associated transactions costs, especially because an intermediary is no longer necessary in the process (Kim & Laskowski, 2017).

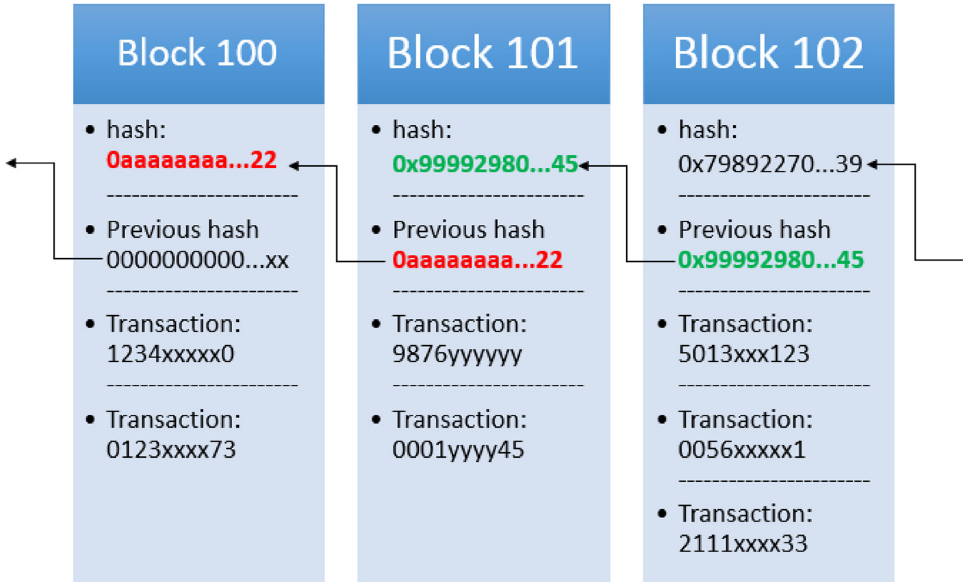

Fig. 1. Blockchain's main properties and operations mode.

A significant characteristic of blockchain is security (Aste et al., 2017), as it has the potential to promote a reconfiguration of all the supply chain relationships. Moreover, blockchain can be combined with other cutting-edge technologies, including the Internet of Things (IoT) (Banerjee et al., 2018), cyber-physical systems (CPS) (Yin, Bao, Zhang, & Huang, 2017) and big data analytics (BDA) (Li et al., 2018). The literature covering these applications keeps developing and may deliver better and more relevant data only in the near future. As the objective of this study is to help understand the behavior of professionals involved in the blockchain adoption process as well as the related facilitating conditions, the next sections will present the theoretical background of blockchain (Kshetri, 2018), the network theory (Mitchell, 1969) and UTAUT/UTAUT2 (2012, Venkatesh et al., 2003), so as to enable the development of supportive hypotheses and a research model.

2.2. Supply chain and network theory perspective

This study follows research by (Carter, Rogers, & Choi, 2015), which considers supply chain is a complex adaptive systems network. Such complexity renders the understanding of the supply networks behavior a critical function (Choi & Dooley, 2009) to any organization. In a supply chain network (SCN), organizations exchange goods, information and services (Choi, Dooley, & Rungtusanatham, 2001), and therefore the actors' relationship within the system is not always so easy to understand. This is why we have resorted to the basic concepts of the network theory (Borgatti & Foster, 2003), and more specifically, to the social network theory. It is defined as "a social network as a specific set of linkages among a defined set of persons, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behavior of the persons involved" (Mitchell, 1969, p.2). This definition implies a relationship with TAMs, the core of the social network theory being the interpretation of the social behavior. Thus, these two theories are suitable to gain an in-depth understanding of blockchain adoption challenges in supply networks.

Prior literature highlights how necessary the social network analysis is for the understanding of relationships within the network (Tichy, Tushman, Fombrun, & Tushman, 1979), such relationships being associated with the strength of their ties (Granovetter, 1973) and embedded with other relations (Granovetter, 1985). In this regard, the development of relationships can lead to cooperation between organizations of the same network (Grandori & Soda, 1995), and even to alliances in the development of common processes and technologies (Gulati, 1998). To understand the complexity of in-network relationships, scholars have been deploying considerable effort to develop models that can support the comprehension of the network structure (Burt, 1980).

Furthermore, the supply networks (Borgatti & LI, 2009) approach is gaining prominence in the supply chain field. For example, knowledge sharing across SCN can be a critical aspect, leading to more resources commitment (Wagner & Buko, 2005), supply chain functions and their integration with demand (Stolze et al., 2015), and risk and uncertainty, notably in global supply networks (Sydow & Frenkel, 2013). In the health sector, care coordination process can be better achieved (Sampson, Schmidt, Gardner, & Van Orden, 2015). In terms of blockchain adoption, there are several challenges associated with, and direct impacts on, the network theory perspective. They include the relationships between organizations, trust, commitment, knowledge exchange, etc.

2.3. Technology acceptance models (TAMs)

The rapid evolution of information and communication technologies (ICTs) has impacted the acceptance and use of these technologies. Scholars studying management information systems (MISs) have dedicated substantial efforts in developing robust models to help understand adoption behaviors (Al-Sayyed & Abdalhaq, 2016; Davis, 1989; Venkatesh et al., 2003, 2012). Available classic studies endeavored to consider the relationship between individual attitudes and behaviors (Azjen & Fishbein, 1980; Davis, 1989; Fishbein & Ajzen, 1975). Drawing on the TRA concepts (Azjen & Fishbein, 1980). Davis (1989) proposed the technology acceptance model (TAM) to help understand the individual behaviors in IT acceptance and adoption. This seminal study was focused on two constructs, namely perceived usefulness (PU) and perceived ease of use (PEOU), both of which were also the pillars for other models (Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh, Brown, Maruping, & Bala, 2008).

2.3.1. Unified theory of acceptance and use of technology (UTAUT)

The unified theory of acceptance and use of technology (UTAUT) was proposed (Venkatesh et al., 2003) as a synthesis of eight models from prior acceptance literature. These include: TAM (Davis, 1989); theory of reasoned action (TRA) (Fishbein & Ajzen, 1975); motivational model (MM) (Davis, Bagozzi, & Warshaw, 1992); theory of planned behavior (TPB) (Ajzen, 1991); combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995), model of PC utilization (MPCU) (Thompson, Higgins, & Howell, 1991); innovation diffusion theory (IDT) (Moore & Benbasat, 1991); and social cognitive theory (SCT) (Compeau & Higgins, 1995). In the UTAUT model, the authors modeled performance expectancy, effort expectancy, social influence, and facilitating conditions as exogenous constructs for predicting the behavioral intention and use. As a result, we have set a model by adapting the UTAUT and integrating two new constructs (blockchain transparency, and trust of supply chain stakeholders) (see Appendix for constructs definitions). Our model does not utilize the moderator's variables (i.e., gender, age, experience, and voluntariness of use) of the original UTAUT model (Dwivedi, Rana, Janssen et al., 2017; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2017).

The UTAUT is an influential model in several research fields, and the original model has been used in various studies and has inspired scholars to propose some modifications. For instance, the UTAUT has been adapted or modified in social networking apps (Chua, Rezaei, Gu, Oh, & Jambulingam, 2018), in cloud services utilization by teachers (Wang, 2017) and in systems by government employees adopting new technologies and processes (Batara, Nurmandi, Warsito, & Pribadi, 2017). A significant extension of the UTAUT, the so-called UTAUT2, was proposed by (Venkatesh et al., 2012), who incorporated three new constructs: hedonic motivation, price value, and habit. Since then, the UTAUT2 model has been used with success in diverse contexts (Farooq et al., 2017; Hew, Lee, Ooi, & Wei, 2015; Makanyeza & Mutambayashata, 2018). In order to achieve the aims of this study, it has appeared to us that the network theory and the UTAUT are suitable approaches to be used. In fact, while the UTAUT helps to better understand the main employees' motivations for blockchain adoption, the network theory is well suited for explaining how external variables can influence technology adoption.

3. Research model and hypotheses

Drawing on the literature on TAM and its extensions, blockchain, SCM and the network theory, we derived a model (Fig. 2) to understand the role of blockchain adoption in the supply chain field. Understanding blockchain adoption implies that we grasp the professional behavior in inter-firm, but also how this behavior can be significantly influenced by the entire supply chain network relationships. Consequently, the network theory supports our argumentation in this regard, mainly given the complexity of the inter-firm relationships (Granovetter, 1973; Tichy et al., 1979), cooperation (Grandori & Soda, 1995), and the necessary partnerships (Gulati, 1998). Considering the nascent development of blockchain technologies, all constructs were mainly derived from the extant literature on UTAUT, networks and supply chain theories.

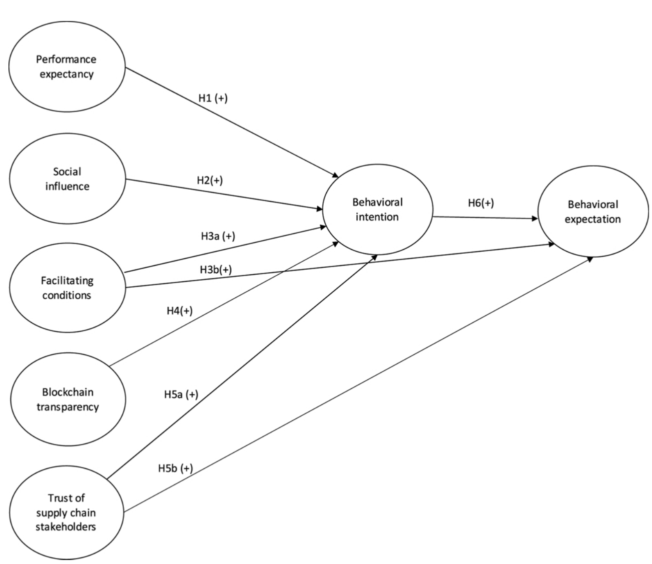

Fig. 2. Research model.

Upon review, constructs such as performance expectancy, social influence, and facilitating conditions were identified as predictors of behavioral intention and behavioral expectation (adopted from the literature on UTAUT), as well as of blockchain transparency and trust of supply chain stakeholders (derived from the literature on networks and supply chain). In the Appendix, we detailed the set of questions for each construct. The performance expectancy (PEXP) indicators are related to the improvement of expectancy in job activities that blockchain can bring for the SCM professionals; social influence (SINF) is made of questions that are related to the possible influence exerted by coworkers, family, and so forth, to make them adopt blockchain; facilitating conditions (FCON) had questions related to how the infrastructure of organizations is made to support blockchain transactions; blockchain transparency (BTRAN) has questions connected to the exchange and visibility of information between organizations; trust among supply chain stakeholders (SCTRU) reflects the level of confidence that blockchain can bring to the transactions and their actors; finally, while behavioral intention (BINT) has questions associated with the intention to adopt blockchain, behavioral expectation (BEXP) is concerned with questions that show the subjective probability for supply chain professionals performing a behavior in favor of blockchain adoption.

A recent study on mobile banking adoption (Oliveira, Faria, Thomas, & Popovič, 2014) developed a UTAUT-based model combined with the task technology fit (TTF) and the initial trust model (ITM). The authors highlighted that effort expectancy construct was not statistically significant in explaining the behavioral intention. Also, more recently, Batara et al. (2017) showed that effort expectancy was not a good predictor of e-government adoption in Indonesia. Because of this, our modified UTAUT does not include effort expectancy.

In the same vein, following recent studies resorting only on a subset of the model, the moderators were dropped (Dwivedi, Rana, Janssen et al., 2017; Dwivedi, Rana, Jeyaraj et al., 2017; Rana, Dwivedi, Lal, Williams, & Clement, 2017; Rana, Dwivedi, Williams, & Weerakkody, 2016). The main reason for this exclusion is the lack of variation in adoption and use as a result of moderators (Dwivedi, Rana, Janssen et al., 2017; Dwivedi, Rana, Jeyaraj et al., 2017). In addition, although our survey's respondents have some experience (Batara et al., 2017; Oliveira et al., 2014) in the area of blockchain, we excluded the construct "usage behavior" (UB) (Batara et al., 2017; Oliveira et al., 2014), as the technology is still new and has not yet lured a significant degree of awareness.

Finally, our model utilizes behavioral intention (BINT) as a predictor of behavioral expectation (BEXP) (Maruping, Bala, Venkatesh, & Brown, 2017; Venkatesh et al., 2008). According to Venkatesh et al. (2008), p.486), "Behavioral expectation […] reflects the strength of the focal behavioral intention over other (competing) behavioral intentions". This implies that "BINT will lead to formation of BEXP" [… and that] this further reinforces the idea that BEXP reflects both internal and external factors in predicting behavior" (Maruping et al., 2017, p.628). Fig. 2 points out the research model.

3.1. Performance expectancy

Performance expectancy (PEXP) is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). In our study context, performance expectancy refers to the degree to which an employee perceives that using the blockchain technologies will improve their productivity and performance. The individual (employee's) motivation to accept and use a new technology is related to his/her perception of some advantages (including the useful level) of the technology in his or her job routine (Davis, 1989; Venkatesh et al., 2003). Thus, blockchain applications have generated high expectations in terms of improvements in supply chain activities, ranging from efficiency and product quality and to other supply chain key process improvements (Kshetri, 2018). Additionally, blockchain can leverage its decentralized status (lack of central intermediary for transaction validation) to minimize process complexity and uncertainty, especially with operations based on smart contracts (Kim & Laskowski, 2017). Prior literature (UTAUT/2) reported that the intention of individuals to use and adopt a technology depends significantly on performance expectancy (Alalwan, Dwivedi, & Rana, 2017; Riffai, Grant, & Edgar, 2012; Venkatesh et al., 2003; Venkatesh et al., 2012; Weerakkody, El-Haddadeh, Al-Sobhi, Shareef, & Dwivedi, 2013). Therefore, we propose the following hypothesis:

H1. *Performance expectancy positively affects the behavioral intention to adopt blockchain.*

3.2. Social influence

Social influence (SINF) is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p.451). For the purpose of this study, social influence will refer to the extent to which the employee comprehends the relevance of why others believe they should use the blockchain technology. Previous studies highlighted that, at the individual level, SINF is impacted by the opinions and acts of colleagues, friends and family members (Irani, Dwivedi, & Williams, 2009; Venkatesh & Brown, 2001). Recent studies have shown how important SINF is in systems adoption. For instance, SINF plays a key role in the adoption of Internet-based banking (Martins, Oliveira, & Popovič, 2014; Zhang et al., 2018) and mobile government services (Ahmad & Khalid, 2017; Weerakkody et al., 2013). Blockchain integrated into SCN also needs a collaboration between supply chain members (Bartlett, Julien, & Baines, 2007; Zhu, Song, Hazen, Lee, & Cegielski, 2018) because the existing relationships create a significant influence on whether to adopt blockchain across the network. Hence, we propose the following hypothesis:

H2. *Social influence positively affects the behavioral intention to adopt blockchain.*

3.3. Facilitating conditions

Facilitating conditions (FCON) are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). In our study, they will refer to employee's understanding of the resources that are available in organizations to support the use of blockchain. In line with prior literature, FCON (e.g. computers, internet speed, integration with other systems) influence the adoption and use of the technology (Huang et al., 2012; Oliveira et al., 2014; Sabi, Uzoka, Langmia, & Njeh, 2016; Venkatesh et al., 2003, 2012). In a supply chain context, the transactions supported by blockchain technologies are stored in the cloud. This represents a significant non-barrier adoption in relation to infrastructure costs. Additionally, the blockchain infrastructure stores a copy of the transactions, thus supporting a query at any time and enabling the traceability of the products and/or services to supply chain members in an easy way (Francisco & Swanson, 2018; Tian, 2017). Therefore, we propose the following hypotheses:

H3a. *Facilitating conditions positively affect the behavioral intention to adopt blockchain.*

H3b. *Facilitating conditions positively affect the behavioral expectation for blockchain adoption.*

3.4. Blockchain transparency

Transparency in supply chain context can be defined as "how supply chain information is communicated to stakeholders" (Morgan et al., 2018, p.961). In our study, blockchain transparency (BTRAN) refers to the models through which an organization communicates and reports its action to its relationships across their supply chain network, so as to support the visibility of the operations at all levels. In an SCN perspective, blockchain can improve the transparency and accountability (Biswas et al., 2017; Kshetri, 2018; Lu & Xu, 2017). As a result, our study argues that blockchain transparency is a significant predictor of behavioral intention of use blockchain. Also, blockchain transparency can enhance the SCN members' cooperation, thus provoking significant transformation in the industry and in the society at large (Aste et al., 2017). Therefore, we set forth the following hypothesis:

H4. *Blockchain transparency positively affects the behavioral intention to blockchain.*

3.5. Trust of supply chain stakeholders

Trust can be defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer, Davis, & Schoorman, 1995, p. 712) This research will be referring to trust of supply chain (SCTRU) stakeholders as the willingness that two or more organizations within the supply chain network are vulnerable to each other and uphold each other's expectations. Trust is a fundamental aspect in all business models. Its influence on technology acceptance model constructs is well demonstrated in the literature (Liébana-Cabanillas et al., 2017; Lin, 2011; Riffai et al., 2012; Wu et al., 2011), with significant data helping to understand trust effect in several contexts (Wu et al., 2011). The social network approach is well recommended for grasping the organization's requirement about the deep understanding of the relationships dynamics (Granovetter, 1973; Tichy et al., 1979). Supply chains are characterized by multiple relationships and a certain level of complexity, and as a result, cooperation across the network becomes an essential variable to most organizations, which implies that such entities have to develop coordination tools to support this interaction (Grandori & Soda, 1995). In a supply chain context, relationships between organizations are a fundamental to their operations. For example, a relationship involving information sharing is critical for operations performance. Unfortunately, the supply chain network generally lacks transparency among the members, which represents a considerable difficulty for organizations (Lamming, Caldwell, Harrison, & Phillips, 2001). An efficient solution to this is the integration of blockchain technologies, as they can minimize uncertainty and empower transparency throughout the entire supply chain (Biswas et al., 2017; Lu & Xu, 2017), as well as supply chain traceability (Jeppsson & Olsson, 2017). Moreover, blockchain can improve the level of trust between supply chain members, as indicated by recent studies (Kano & Nakajima, 2018; Kshetri, 2018; Reyna, Martín, Chen, Soler, & Díaz, 2018; Zou et al., 2018). Therefore, we propose the following hypotheses:

H5a. *Trust between supply chain stakeholders positively affects behavioral intention to adopt blockchain.*

H5b. *Trust between* supply *chain stakeholders positively affects behavioral expectation for blockchain adoption.*

3.6. Behavioral intention and expectation

Behavioral intention (BINT) is defined "as the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior (Warshaw & Davis, 1985, p. 214). In this study, behavioral intention refers to the employee' ability to perform a behavior toward blockchain use. BINT exerts a direct influence on the use of technologies (Ajzen, 1991; Venkatesh et al., 2003; Weerakkody et al., 2013). Therefore, our study argues that BINT predicts behavioral expectation (BEXP), the latter being defined as the employee's evaluation of the probability to perform a particular behavior associated with the use of blockchain in the future. Prior UTAUT studies reported the behavioral intention construct has an impact on behavioral expectation construct (Maruping et al., 2017; Venkatesh et al., 2008). In this perspective, Venkatesh et al. (2008), p. 486) argue that "The motivational drive to perform a target behavior stems from an individual's internal evaluation of the behavior". Thus, the individual behavioral intention is associated with his or her internal evaluation. Consequently, behavioral intention precedes behavioral expectation, that is, "Behavioral expectation, therefore, reflects the strength of the focal behavioral intention over other (competing) behavioral intentions" (Venkatesh et al., 2008, p. 486). In line with previous studies reporting behavioral intention in technology usage (Maruping et al., 2017; Venkatesh et al., 2008), we propose the following hypothesis:

H6. *Behavioral intention positively affects behavioral expectation for blockchain adoption.*

4. Research methodology

4.1. Sampling design and data collection

The appendix shows the constructs and their definitions. We adapted scales from prior literature (2012, Maruping et al., 2017; Mayer et al., 1995; Morgan et al., 2018; Venkatesh et al., 2003) and derived to this study context. All constructs were measured by a 7-point Likert scale (i.e., strongly disagree – strongly agree) (Akter, Fosso Wamba, & Dewan, 2017). The survey pretesting was realized by 22 scholars and professionals involved in blockchain-enabled supply chain initiatives.

The final questionnaire was managed by a leading market research provider called Research Now (http://www.researchnow.com/en-US.aspx) from April 19, 2018 to May 24, 2018. For each sample, an invitation letter explaining the overall objectives of the study was sent to supply chain professionals with at least three years of experience in the area of blockchain, to participate in the study. For the Indian study, 974 members accepted to participate in the study. After analysis, 344 responses (response rate of 35.32%) were deemed valid. For the USA case, 6131 members agreed to participate in the study. But only 394 responses were considered to have been appropriately filled out and therefore suitable for supplementary analysis (response rate of 6.43%).

4.2. Nonresponse, common method Bias and endogeneity

We analyzed the nonresponse bias between early and late respondents (Armstrong & Overton, 1977; Tsou & Hsu, 2015). To assess nonresponse bias, a *t*-test was performed (Tsou & Hsu, 2015), and no statistical differences was detected in the scale items from each construct. Therefore, we conclude that the nonresponse bias did not affect the model. In the same light, a common method bias (CMB) can inflate the relationships between the exogenous and endogenous variables, with a single respondent (Podsakoff & Organ, 1986). To prove that CMB did not affect the model, we employed a Harman's one-factor test (Alalwan et al., 2017; Podsakoff & Organ, 1986; Tsou & Hsu, 2015; Wang, Wang, & Lin, 2018). CMB was ultimately proved to unlikely affect the results. Furthermore, the structural model recursivity can generate endogeneity (Dubey et al., 2018; Lai, Sun, & Ren, 2018), that is, the cross-sectional data can result in a misspecified model because the variance in an exogenous variable can be endogenous to the model (Guide & Ketokivi, 2015). Thus, we employed a Ramsey regression equation error test (Lai et al., 2018), and discovered that the endogeneity was not a problem in our model.

Table 1
Demographic profile (n = 738).

	India		USA	
	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

4.3. Data analysis

We employed PLS-SEM to analyze the proposed conceptual model (Akter et al., 2017; Shim, Lee, & Kim, 2018; Sun & Teng, 2017). PLS-SEM is gaining prominence in the study of social science issues, and it is suitable for large and small sample sizes, as well as for nonnormal data (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). Additionally, PLS-SEM is fit for exploratory research (Godinho Filho, Ganga, & Gunasekaran, 2016; Hair et al., 2014; Hazen, Bradley, Bell, In, & Byrd, 2017; Yadlapalli, Rahman, & Gunasekaran, 2018). This may explain why supply chain studies have been increasingly using PLS-SEM (Chae, Olson, & Sheu, 2014; Han, Wang, & Naim, 2017; Jeble et al., 2017; Tsanos & Zografos, 2016). In this study, our conceptual model causality goes from constructs to items, thus giving a reflective model (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016).

Table 1 shows the respondents' demographic profile. The distribution of male and female respondents was similar in India and the USA: 70.1 and 72.3 percent, and 29.9 and 27.7 percent, respectively. In terms of age, most respondents in India were between 26 and 33 years old (51.2 percent), while most respondents in the USA were between 34 and 41years old (39.6 percent). Considering the education level, 52.6 percent of respondents in India and 33.0 percent of those in the USA held a postgraduate degree, against 34.0 percent and 26.6 percent for holders of a bachelor's degree. In India, 40.1 of respondents were working in an organization for at least 2–5 years, followed by those (38.1 percent) with 6–10 years' experience. In the USA context, the majority (34.5 percent) of respondents had been working in an organization for at least 6–10 years, and 20.6 percent of respondents had 2–5 years' experience. Also, the respondents with at least 11–15 years of experience, 16–20 years and over 20 years were more expressive in the USA case, their percentage being19.0, 12.9, and 10.7 percent, respectively. By contrast, in the Indian case, the percentages for the respondents with the same aforementioned age brackets were 14.2, 2.3, and 1.5, respectively. The dominant industry of respondents in India is manufacturing (35.2 percent), while in the USA we have transportation, manufacturing, and construction, with 16.2, 14.7 and 14.5 percent, respectively.

4.4. Findings

This study used SmartPLS 3.0 to analyze the proposed model (Hair et al., 2017; Han et al., 2017; Ringle, Wende, Sven, & Becker, 2015; Svensson, Ferro, Hogevold, Padin, & Sosa Varela, 2018). Findings are presented below, together with the measurement model and the structural model.

4.4.1. Measurement model

Our model was developed in line with the prior literature. Thus, the constructs and its indicators were chosen because they are recognized as suitable for better explaining technology behavior adoption (2012, Brown, Dennis, & Venkatesh, 2010; Maruping et al., 2017; Venkatesh et al., 2003). As regards the indicators related to blockchain transparency and trust, they were chosen according to the well-established literature on supply chain (Mayer et al., 1995; Svensson, 2001; Whipple, Griffis, & Daugherty, 2013). For instance, the four indicators related to SINF show how likely a supply chain professional can influence blockchain adoption. The four FCON indicators reflect organizations' infrastructure and capabilities to support blockchain technologies; PEXP also has four indicators, and they all contribute to capture the professional's expectancy in relation to their job improvement (e.g., productivity); the four BTRAN indicators are associated with the information shared across the supply chains, thus enabling high levels of transparency; The four indicators of SCTRU show the level of trust among supply chain members when they make blockchain-enabled transactions. The BINT has three indicators and reflects the intention to use blockchain in a short time. As for the BEXP, it also has three indicators and reflects both internal and external factors in predicting behavior. In this regard, we believe that the indicators chosen are suitable to the blockchain context.

Table 2 shows the outer loadings. It clearly appears that all have a value higher than the threshold value of 0.7 (Hair et al., 2017), except FCON3 with 0.685. Table 3 presents the Cronbach's alpha values, composite reliability and AVE values of all constructs. All values presented in Table 3 exceeded or were equivalent to the threshold values, as they are respectively at 0.70, 0.70 and 0.50 (Guadagnoli & Velicer, 1988; Hair et al., 2017; Nunnally, 1978; Wang, Yeh, & Liao, 2013). Consequently, the utilization of the all contructs in the proposed research model is well justified. Moreover, the AVE for each construct exceeding 0.50 shows that the items variance observed accounted for hypothesized constructs (Y. S. Wang et al., 2013). Furthermore, we tested the discriminant validity of the model (Table 4), which showed for each construct an AVE square root greater than the correlations

Table 2
Outer loadings.

Construct	Item	Loadings	
		India	USA
BEXP	BEXP1	0.866	0.930
	BEXP2	0.880	0.925
	BEXP3	0.831	0.927
BINT	BINT1	0.879	0.931
	BINT2	0.875	0.931
	BINT3	0.858	0.926
BTRAN	BTRAN1	0.841	0.854
	BTRAN2	0.799	0.902
	BTRAN3	0.839	0.883
	BTRAN4	0.809	0.878
FCON	FCON1	0.844	0.863
	FCON2	0.846	0.870
	FCON3	0.685	0.741
	FCON4	0.799	0.849
PEXP	PEXP1	0.838	0.893
	PEXP2	0.838	0.873
	PEXP3	0.838	0.884
	PEXP4	0.819	0.838
SCTRU	SCTRU1	0.870	0.885
	SCTRU2	0.822	0.910
	SCTRU3	0.847	0.915
	SCTRU4	0.808	0.901
SINF	SINF1	0.844	0.861
	SINF2	0.830	0.872
	SINF3	0.818	0.882
	SINF4	0.784	0.865

BEXP (Behavioral Expectation), BINT (Behavioral Intention), BTRAN (Blockchain Transparency), FCON (Facilitating Conditions), PEXP (Performance Expectancy), SCTRU (Trust of Supply Chain Stakeholders), SINF (Social Influence).

Table 3
Cronbach's Alpha, CR and AVE values.

Construct	Cronbach's Alpha		Composite Reliability (CR)		Average Variance Extracted (AVE)	
	India	USA	India	USA	India	USA
BEXP	0.823	0.919	0.894	0.948	0.739	0.860
BINT	0.840	0.921	0.904	0.950	0.758	0.863
BTRAN	0.841	0.902	0.893	0.932	0.676	0.773
FCON	0.808	0.851	0.873	0.900	0.634	0.693
PEXP	0.853	0.895	0.901	0.927	0.695	0.761
SCTRU	0.857	0.924	0.903	0.946	0.701	0.815
SINF	0.837	0.893	0.891	0.926	0.671	0.757

Table 4
Discriminant validity.

Construct	1	2	3	4	5	6	7
India							
BEXP	0.859						
BINT	0.776	0.871					
BTRAN	0.672	0.635	0.822				
FCON	0.605	0.656	0.657	0.796			
PEXP	0.745	0.739	0.767	0.704	0.833		
SCTRU	0.579	0.600	0.685	0.697	0.690	0.837	
SINF	0.686	0.712	0.716	0.701	0.651	0.673	0.819
USA							
BEXP	0.927						
BINT	0.877	0.929					
BTRAN	0.707	0.706	0.879				
FCON	0.765	0.766	0.762	0.832			
PEXP	0.808	0.792	0.798	0.777	0.872		
SCTRU	0.706	0.728	0.754	0.749	0.783	0.903	
SINF	0.724	0.723	0.776	0.795	0.763	0.763	0.870

Table 5
Path coefficients.

Hypothesis	Path	INDIA				USA			
		β	std. dev.	t-statistics	p-value	β	std. dev.	t-statistics	p-value
H1	PEXP - > BINT	0.472	0.082	5.763	0.000	0.393	0.088	4.439	0.000
H2	SINF - > BINT	0.386	0.074	5.188	0.000	0.092	0.099	0.923	0.356
H3a	FCON - > BINT	0.105	0.072	1.461	0.144	0.285	0.074	3.874	0.000
H3b	FCON - > BEXP	0.098	0.068	1.436	0.151	0.195	0.066	2.955	0.003
H4	BTRAN - > BINT	−0.060	0.090	0.665	0.506	0.002	0.092	0.023	0.982
H5a	SCTRU - > BINT	−0.017	0.072	0.241	0.810	0.136	0.080	1.704	0.089
H5b	SCTRU - > BEXP	0.131	0.060	2.187	0.029	0.065	0.050	1.295	0.195
H6	BINT - > BEXP	0.633	0.069	9.195	0.000	0.681	0.056	12.263	0.000

between that particular construct and all other constructs (Fornell & Lacker, 1981); this, therefore, confirms the discriminant validity (Fosso Wamba, 2018).

4.4.2. Structural model

Table 5 presents the results regarding the path coefficients, std. dev., *t*-values, and *p*-values for the strucutural model, for each country. PEXP had a significant positive effect on BINT in both India and the USA ($\beta = 0.472$, $t = 5.763$, $p = 0.000$, and $\beta = 0.393$, $t = 4.439$, $p = 0.000$), respectively for the two contexts. Thus, H1 was supported in both countries. SINF was found to have a significant positive effect on BINT in India ($\beta = 0.386$, $t = 5.188$, $p = 0.000$), unlike in the USA case, where there was a positive non-significant effect ($\beta = 0.092$, $t = 0.923$, $p = 0.356$). Therefore, H2 was supported for India data and non supported for the USA. This finding indicates that there are clear differences in blockchain adoption behavior across the countries under study. A non-significant positive effect of FCON on BINT and of FCON on BEXP was observed when using India's data ($\beta = 0.105$, $t = 1.461$, $p = 0.144$ for the former; and $\beta = 0.098$, $t = 1.436$, $p = 0.151$ for the latter). In this case, H3a and H3b was not supported for the Indian case. However, the effetcts of FCON on BINT and BEXP were found to be significantly positive when using the USA data ($\beta = 0.285$, $t = 3.874$, $p = 0.000$; and $\beta = 0.195$, $t = 2.955$, $p = 0.003$). Surprinsigly, we can observe a non-significant negative effect of BTRAN on BINT for India, and the contrary for the USA(β = -0.06, $t = 0.665$, $p = 0.506$; and $\beta = 0.002$, $t = 0.023$, $p = 0.982$). Therfore, H4 was not supported the two countries (India and the USA). We can observe that H5a (SCTRU on BINT) was not supported for the same countries, where β = -0.017, $t = 0.241$, $p = 0.810$; and $\beta = 0.136$, $t = 1.704$, $p = 0.089$, respectively. However, the effect of SCTRU on BEXP was found to be positive for India and the USA ($\beta = 0.131$, $t = 2.187$, $p = 0.029$; and $\beta = 0.065$, $t = 1.295$, $p = 0.195$). However, H5b was supported only for India's data. Finally, as expected, we have a significant positive effect of BINT on BEXP for the two contexts (India and USA) ($\beta = 0.633$, $t = 9.195$, $p = 0.000$, and $\beta = 0.681$, $t = 12.263$, $p = 0.000$), which indicates that H6 was supported. Lastly, Table 6 shows that the proposed model accounted for 63.9 and 69.2 percent of the variance in BINT, respectively for India and the USA, and 62.3 and 79.0 percent of the variance in BEXP, respectively for the same countries. Regarding BINT, the variance found is close to the benchmarks (2012, Venkatesh et al., 2003) while BEXP results corroborate those by Maruping et al. (2017).

Table 6
R-square result.

Dependent constructs	INDIA		USA	
	R Square	R Square Adjusted	R Square	R Square Adjusted
BEXP	0.627	0.623	0.792	0.790
BINT	0.644	0.639	0.696	0.692

5. Discussion

Based on theories concerning technology acceptance models (TAMs) (Davis, 1989), with special focus on UTAUT and UTAUT2 (Venkatesh et al., 2012; Venkatesh et al., 2003), we theoretically developed and empirically validated a proposed research model to help understand the individual behavior behind blockchain adoption and use. Unfortunately, prior literature on IT adoption or even on SCM does not, to the best of our knowledge, include outstanding research on blockchain adoption using the UTAUT model or its variation. This is why our model presents new constructs that may help to predict behavioral intention and behavioral expectation in blockchain adoption in the SCM context. Thus, we incorporated BTRAN as a predictor of BINT (H4), and SCTRU as a predictor of BINT (H5a) and BEXP (H5b).

Our analysis showed that the variance in BINT was 63.9 and 69.2 percent for India and the USA, respectively. These values are higher than original UTAUT (Venkatesh et al., 2003) and similar to UTAUT2 (Venkatesh et al., 2012). Additionally, the BEXP variance was 62.3 and 79.0 percent for India and the USA and therefore looked very close to the results reported in a recent study (Maruping et al., 2017). In line with the prior literature, PEXP (H1) had a significant positive effect on BINT (Maruping et al., 2017; Venkatesh et al., 2003), and BINT (H6) appeared to be a significant predictor (Maruping et al., 2017) of BEXP in both the Indian and American contexts for blockchain adoption.

Moreover, the results confirm that SCTRU (H5b) is an important predictor of BEXP only for India's case. Surprisingly, our findings indicated that SCTRU (H5a) is not a predictor of BINT for the two contexts, although with a non-significant positive effect in the USA. These results suggest that trust between supply chain stakeholders does not affect blockchain adoption in both cases. Besides, BTRAN (H4) has a non-significant negative influence on BINT in India, and a non-significant positive effect on the same in the USA. Furthermore, consistent with prior literature, our results confirm that PEXP (H1) is an important predictor of BINT (Oliveira et al., 2014; Venkatesh et al., 2012; Venkatesh et al., 2003; Weerakkody et al., 2013) in both countries. Lastly, FCON is a predictor of BINT (H3a) and BEXP (H3a) only in the USA. Thus, these findings reinforce the existence of differences in blockchain adoption behavior across the countries.

The values of R^2 accounted in behavioral intention (63.9% and 69.2%, for India and the USA, respectively) exceeded the percentages recommended in the literature. For instance, 20% (Chin, 1998; Martins et al., 2014) and 30% (Chin, 1998). In addition, our findings are very close to those of a recent empirical study of blockchain adoption (Kamble et al., 2018) that registered a variance rate of 68.7% in the behavioral intention to use blockchain in the supply chain.

Our major findings indicate interesting similarities and differences between the countries analyzed. For instance, BTRAN (H4) was not supported in both countries, possibly because of the degree of awareness of the technology among supply chain professionals. For example, Kamble et al. (2018) found that the SCM respondents had a low level of blockchain awareness, and this evidently impacted the survey's return. Moreover, PEXP was supported in India and the USA, where PEXP (H1) is a sensible variable for a cutting-edge technology and highly influences blockchain adoption by supply chain professionals. Such findings are in line with those of prior studies that used this construct (Alalwan et al., 2017; Weerakkody et al., 2013). On the other hand, FCON (H3a and H3b) was not supported in the Indian context, suggesting that in developing countries, facilitating conditions play a key role in repulsing the adoption of blockchain. It also suggests that developed countries have all necessary facilitating conditions to support blockchain adoption in SCM.

Furthermore, our results show that SCTRU (H5b) has a significant influence on BEXP only for the Indian case. Again, it reinforces the differences in individual behaviors to adopt blockchain in SCM. However, while some studies reported trust as a predictor of BINT (Liébana-Cabanillas et al., 2017; Weerakkody et al., 2013), our findings indicated that trust (H5a) in the context of the supply chain (SCTRU) does not affect the behavioral intention to adopt blockchain. Lastly, although social influence is being reported as a good predictor of BINT (Venkatesh et al., 2012, 2003), the SINF (H2) findings indicated that social influence has a significant positive effect in blockchain adoption only in India. This suggests that in emerging economies, colleagues and family members exert an important influence on BINT. As for our results for the USA, they are aligned on those of a recent study on the adoption of mobile banking (Alalwan et al., 2017), which did not indicate any effect of the SINF on BINT.

In short, our results bring valuable contributions to the theory and for practice. The validated model showed important relationships with strong coefficients. Although the adoption of blockchain in logistics and supply chains is quite recent, the findings suggest essential insights that may be explored by managers involved in blockchain adoption projects, including consideration for country's particularities the infrastructure of adopting organizations (e.g., FCON H3a and H3b were not supported in India). Another point is that, according to the results obtained, social influence could not impact blockchain adoption only in India. This clearly reinforces the fact that blockchain adoption varies from one country to another, and suggests that the opinion of co-workers and family members on blockchain adoption counts much more than expected in developing countries and triggers real influence. In addition, despite the low level of infrastructure in emerging economies infrastructure, the results showed that their influence on blockchain adoption is real only in developed countries as compared to developed countries. Another interesting finding was that the SCTRU was proved to influence behavioral expectation for blockchain adoption only on India, thus suggesting that trust among supply chain stakeholders actually affects the expectation to adopt blockchain only in emerging economies.

5.1. Implications for research

In this study, we developed a model to enable a better understanding of adoption behavior at the individual level for this disruptive and emerging technology (blockchain) in the SCM context. For the development of the IT adoption field and that of SCM, and considering the expected impacts of blockchain, our study appears as a valuable contribution. While our research model was derived from prior literature acceptance models (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012), we furthered research and attempted to bridge a real gap in the literature on blockchain adoption in ISs and SCM. And in this case, we applied PLS-SEM in a cross-country context; in India and the USA. Our proposed model provides the literature on IT adoption and SCM with important insights that should help scholars and practionners to better understand and advance research on how indivuals behave when they adopt blockchain. Following results from the proposed model and the overall study, indivuals do not behave the same way in India and the USA when it comes to adopting blockchain. Scholars can extend this study by applying or adapting our model to a new set of countries, taking into account their various distinctive characteristics. Moreover, they may deepen research on our results regarding BTRAN (H4) and SCTRU (H5a) as non-predictors of BINT, as we found out for the cases of India and the USA.

5.2. Implications for practice

Our findings bring essential insights for IS and SCM practitioners. First, this study presents a model based on the literature on classic IT adoption that is further adapted to blockchain adoption in the supply chain context. Second, our statistical results show interesting differences in blockchain behavior adoption in the supply chain management context. For instance, FCON (H3a) and (H3b) was supported only in the USA; the effect of SCTRU on BEXP (H5b) and SINF (H2) on BINT was supported only in India. Thus, it reinforces a recent finding (Kamble et al., 2018) on the low level of blockchain awareness in the supply chain context. Consequently, managers are informed of challenges and opportunities they will be facing when implementing blockchain projects.

Third, BTRAN (H4) and SCTRU (H5a) were found to have an insignificant effect on BINT, thereby suggesting that supply chain professionals in India and the USA are reluctant to exchange data with their supply chain members. Such behavior was already reported in a recent research work by Kamble et al. (2018), where the "insecurity" construct was not supported for predicting perceived usefulness and perceived ease of use.

Regarding the influence and role of facilitating conditions, this study provided supply chain professionals involved in blockchain projects with useful clues. One of them is that in emerging countries where organizations face a shortage of IT infrastructure and Internet speed, among other shortcomings, the FCON acts as a demotivator variable in blockchain adoption. A derived implication is that organizations and managers have to put in important efforts in order to develop the infrastructure that is needed to facilitate the adoption and implementation of blockchain adoption.

Other important implications are suggested for CIOs and top managers involved in blockchain projects. For instance, they should be henceforth better aware of the fact that facilitating conditions (H3a) and (H3b) influence blockchain adoption behavior or do not do so, depending on the peculiarities of each country (in our case, there was influence in the USA, but the contrary ocurred in India). Also, the results highlight the importance of the performance expectancy (H1) regarding behavioral intention, in India and the USA. Therefore, CIOs and practitioners should consider this critical finding in their project-related decisions, in line with the impact of blockchain usefulness and productivity in their operations. The last strong practical implication of this study is neccesity for blockchain adopting organizations and developers to pay attention to how the system can maximize the users' productivity.

5.3. Limitations and future research

This study has several limitations to be addressed in the future research. Firstly, our model considers a limited number of constructs to explain blockchain adoption in the SCM context. Future studies may consider extending our model by integrating information systems benefits for individuals (ISBI) (DeLone & McLean, 1992, 2003) and the TJW framework (Sun & Teng, 2017). Secondly, our study does not include neither the effort expectancy construct nor the UTAUT moderators. It is expected that such shortcomings may be mitigated by future research. Thirdly, the fact that our model was tested only in two countries does not give us the adequate leeway to generalize our results worldwide. Thus, it opens a research avenue that will consist in applying a comparative blockchain adoption modeling in other countries and contexts. They may include national environments such as the BRICS, and developed and emerging economies, etc. Finally, as highlighted in the analysis section, it was discovered that BTRAN (H4) and

SCTRU (H5a) had no influence on BINT. This needs to be more investigated in other cross-country studies.

6. Conclusions

In this paper, we aimed to shed light on blockchain adoption behavior in the SCM field, while taking into account the behavior of the adopters from India and the USA. Our model was developed in accordance with prior IT adoption literature (Davis, 1989; Maruping et al., 2017; Venkatesh et al., 2012; Venkatesh et al., 2003). Our model was estimated using PLS-SEM approach, and the results obtained supported the proposed model. However, it showed important differences in blockchain adoption behavior across the countries under study. We incorporated BTRAN as a predictor of BINT, and SCTRU as a predictor of BINT and BEXP. SCTRU proved to have a positive effect on BEXP only in the Indian context. Other significant findings were related to the influence of facilitating conditions on blockchain adopters; this was the case only in the USA. Blockchain adoption behavior in other countries and contexts (not only IT and SCM) has to be investigated to complete our findings and enable any generalization. In line with a recent blockchain adoption (Kamble et al., 2018), our results showed that the blockchain adoption by logistics and supply chain management professionals is still at its infancy stage. Future studies are therefore called upon to investigate, inter alia, the relationship between blockchain awareness and the adoption of the blockchain applications in the supply chain field.

According to the results obtained, our proposed model was adequately explained, with accounting signficantly in behavioral intention (63.9% and 69.2%, for India and the USA, respectively), while outperforming the UTAUT benchmark (Venkatesh et al., 2003) and similar to UTAUT2 (Venkatesh et al., 2012). Moreover, some results are aligned with those from previous literature on IT adoption. For example, PEXP (H1) influences BINT (Oliveira et al., 2014; Venkatesh et al., 2003, 2012; Weerakkody et al., 2013), and BINT (H6) influences BEXP (Maruping et al., 2017) in both countries for blockchain adoption; FCON (H3a and H3b) showed contrast with adoption literature (Venkatesh et al., 2003, 2012), for the Indian context. Furthermore, we noticed that trust had no effect on BINT, that is, trust (H5a) in the context of the supply chain (SCTRU) had no effect on the behavioral intention to adopt blockchain. As a result, previous relevant studies (Liébana-Cabanillas et al., 2017; Weerakkody et al., 2013) are contradicted. Finally, our study and the proposed model suggest how it is urgent to conduct more studies on blockchain and extend research to many other countries around the world.

Appendix A. Survey instrument

Indicators of the research model

Construct	Cod	Indicators	Adapted from
Social influence (SINF)	SINF1	People who influence my behavior think that I should use blockchain technologies	(Brown et al., 2010; Maruping et al., 2017; Venkatesh et al., 2003, 2012)
	SINF2	People who are important to me think that I should use blockchain	
	SINF3	The senior management of this business has been helpful in the use of blockchain	
	SINF4	In general, the organization has supported the use of the blockchain technologies	
Facilitating conditions (FCON)	FCON1	I have the necessary resources to use blockchain technologies	(Brown et al., 2010; Maruping et al., 2017; Venkatesh et al., 2003, 2012)
	FCON2	I have the knowledge necessary to use blockchain technologies	
	FCON3	Blockchain technologies are not compatible with other systems I use	
	FCON4	A specific person (or group) is available assist in case of blockchain-related difficulties	
Behavioral intention (BINT)	BINT1	I intend to use blockchain technologies in the following months	(Brown et al., 2010; Maruping et al., 2017; Venkatesh et al., 2003, 2012)
	BINT2	I predict I would use blockchain technologies in the following months	
	BINT3	I plan to use blockchain technologies in the following months	
Behavioral expectation (BEXP)	BEXP1	I expect to use blockchain technologies in the following months	(Maruping et al., 2017)
	BEXP2	I will use blockchain technologies in the following months	
	BEXP3	I am likely to use blockchain technologies in the following months	
Performance expectancy (PEXP)	PEXP1	I would find blockchain technologies useful in my job	(Brown et al., 2010; Maruping et al., 2017; Venkatesh et al., 2003, 2012)
	PEXP2	Using blockchain technologies enables me to accomplish tasks more quickly	
	PEXP3	Using blockchain technologies increases my productivity	
	PEXP4	If I use blockchain technologies, I will increase my chances of getting a raise	
Blockchain transparency (BTRAN)	BTRAN1	I believe blockchain enabled-supply chain processes would be transparent	(Awaysheh & Klassen, 2010; Morgan, Richey, et al., 2018)
	BTRAN2	I believe supply chain stakeholders will provide me with deep access to how blockchain enabled-supply chain applications work	
	BTRAN3	I believe supply chain stakeholders will provide me with in-depth knowledge about applications of blockchain in supply chain	
	BTRAN4	I believe I will have opportunities to provide feedback on blockchain enabled-supply chain applications	
Trust of supply chain stakeholders (SCTRU)	SCTRU1	I think I can trust supply chain stakeholders	(Mayer et al., 1995; Svensson, 2001; Whipple et al., 2013)
	SCTRU2	Supply chain stakeholders can be trusted to carry out blockchain transactions faithfully	
	SCTRU3	In my opinion, supply chain stakeholders are trustworthy	
	SCTRU4	I trust supply chain stakeholders to keep my best interests in mind.	

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