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A machine learning based approach for predicting blockchain adoption in supply Chain

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ABSTRACT

The purpose of this paper is to provide a decision support system for managers to predict an organization's probability of successful blockchain adoption using a machine learning technique. The study conceptualizes blockchain technology as a dynamic capability that should be possessed by the organization to remain competitive. The factors influencing the blockchain adoption behavior were modeled using the theoretical lens of the Technology Acceptance Model and Technology-organisation-Environment framework. The findings identify competitor pressure, partner readiness, perceived usefulness, and perceived ease of use as the most influencing factors for blockchain adoption. A predictive decision support system was developed using a Bayesian network analysis featuring the significant factors that can be used by the decision-makers for predicting the probability of blockchain adoption in their organization. The prior probability values reported in the study may be used as indicators by the practitioners to predict their blockchain adoption probability. The practitioner will be required to substitute these probability values (high or low), as applicable to their organization to estimate the adoption probability. The use of the decision support system is likely to help the decision-makers to assess their adoption probability and develop future adoption strategies.

1. Introduction

Organizations with effective supply chains are found to be highly efficient and responsive, and therefore, organizations are continuously in search of innovative technologies that facilitate efficiency improvement within supply chains (Craighead et al. 2007). Given both changing consumers' preferences and dynamic market competition, supply chains are becoming more complex. Factors such as the spread of organizations to different geographic locations, the increasing scope of operations, or unreliable demand patterns and product portfolios, give birth to challenges to these organizations for synchronizing their supply and demand plans (Ojha et al., 2018). Previous studies have shown that emerging technologies facilitates organizations to overcome such challenges through supply chain transformation (Long et al., 2017). Within a digital supply chain, the control of the supply chain must be shared across partners and not owned by a single company. Currently, traditional supply chains are facing various problems, including the issues of transparency, product traceability, and accountability (Min 2019). In such a context, blockchain technology is seen as one of the most promising information technology innovations that will bring enormous improvements to supply chain transactions (Lacity 2018; Kamble et al., 2019; Pazaitis et al., 2017). Indeed, the Word Economic Forum considers blockchain to be among six computing "mega-trends" that are likely to shape the world in the next decade (World Economic Forum 2015). Blockchain technology provides the ability to store data in blocks, which are then added in chronological order, shared, and distributed to all concerned supply chain partners (Angelis and da Silva, 2019; Kshetri 2017; Lacity 2018). Overall, blockchain architecture provides the opportunity for organizations to track and trace their products, providing a highly secured transaction environment helping to solve trust issues

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((Kshetri, 2018).

Blockchain technology is presently spreading across industries, and more and more organizations are exploring ways to match their capabilities when adopting blockchain technology (Janssen et al., 2020). The technology adoption is defined as a sociological model that describes the adoption or acceptance of technology, according to the demographic and psychological characteristics of defined adopter groups (Rogers, 1995). The demographic and psychological characteristics of the users influence the blockchain technology adoption in supply chains (Kamble et al., 2019; Queiroz and Fosso Wamba, 2019). Predominantly, blockchain adoption is driven by the trust factor, which is linked to four areas, including enhanced visibility and traceability, supply chain digitization and disintermediation, improved data security, and smart contracts (Wang et al., 2018; Pereira et al., 2019). The blockchain has not yet reached its optimum maturity level, and organizations should conduct extensive feasibility studies before adoption (Kamble et al., 2019).

Presently, most organizations are in the process of analyzing various factors leading to blockchain adoption, and therefore, it is essential to understand the way individuals behave when adopting such technologies and there is an urgent need to conduct research providing empirical evidence on blockchain adoption (Kamble et al., 2019; Queiroz and Fosso Wamba, 2019). Until recently, most of the studies on blockchain adoption have focused on developing theoretical frameworks and are conceptual (Durach et al., 2020; Min, 2019; Wang et al., 2018; Francisco and Swanson, 2018). There have been some efforts from the researchers to develop and empirically validate frameworks based on Technology Acceptance Model (TAM) (Kamble et al., 2019), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Francisco and Swanson, 2018; Queiroz and Fosso Wamba, 2019; Clohessy et al., 2019). These empirical studies have used Structural Equation Modeling (SEM) to analyze adoption behaviors. SEM fails to provide excellent managerial decision support, given these models are based on linear relationships resulting in poor diagnosis and prediction (Gupta and Kim 2008).

Bayesian network analysis is similar to SEM and depicts the cause-effect is a relationship-based model (Malakmohammadi et al., 2009). Further, in Bayesian network analysis, causal dependencies between constructs are expressed using conditional probabilities based on historical data (Castillo et al., 1997). Compared to SEM, the Bayesian network analysis can be used for prediction and diagnosis using new data on an already developed model and performs better in analyzing non-linear relationships. Nevertheless, the Bayesian network analysis has certain limitations. First, relationships are based on conditional probabilities using historical data, and therefore, it cannot differentiate between a causal relationship and a theoretically unsound relationship (Pearl 1998). Secondly, even if a theoretically sound structural model is forced as Bayesian network analysis, results will lack the ability to providing theoretical explanations (Anderson and Vastag, 2004). Lastly, the lack of ability to distinguish between latent variables and their measurement items (observed variables) is another significant limitation of using Bayesian network analysis.

To overcome the limitations of the SEM and Bayesian network analysis, a two-stage integrated SEM, and Bayesian network analysis was proposed by Gupta and Kim (2008). This combined methodology considers a theoretically developed and empirically validated SEM model and Bayesian network analysis at the hypothetical variable level to build a prediction model. In this study, we extend the work of Gupta and Kim (2008) and use the SEM- Bayesian network to predict blockchain adoption in India. The integrated methodology overcomes the significant limitations of the SEM and Bayesian network analysis and can be used for predicting the future probability of blockchain adoption.

More specifically, the paper aims to explain the intent of blockchain adoption by using the psychological constructs from the literature on technology adoption and build a predictive model to estimate the probability of blockchain adoption. Our study is one of the preliminary studies on blockchain adoption that guides a widely accepted machine learning algorithm to predict the adoption behavior closely related to a theoretical model based on the extension of the TAM framework. In the following section, we present the conceptual background. Then, we present our research model, hypotheses development, and methodology of our study. In the final section, the findings, conclusion, limitations, and future research of blockchain adoption are discussed.

2. Conceptual background

2.1. Blockchain technology in supply chain

In a blockchain, transactions are recorded and maintained in real-time in an audit-proof manner, and changes are authenticated based on the consensus of the parties involved in transactions. Once transactions are approved by all concerned parties (nodes), it cannot be modified or deleted, which provides the benefits of data integrity and security. Increased safety, transparency, traceability, and efficiency in supply chain transactions can be achieved through blockchain adoption (Kamble et al., 2019; Kshetri 2018). Blockchain deployment outside finance services has been mostly experimental (Kshetri 2018), and emphasis has been on blockchain technology itself rather than on the issues of selection and adoption (Angelis and da Silva, 2019). With this in mind, blockchain also offers increased supply chain integration, which leads to a better overall supply chain performance (Kshetri 2018). Kshetri and Loukoianova (2019) report that existing technology may be economically beneficial for high-value products and present challenges for deploying it for low priced products. The supply chain enabled with blockchain technology leads to increased customer confidence by providing them the benefits of real-time tracking of the products, reduction in product movement costs, highly secured transactions, and protect product counterfeiting (Kamble et al., 2020). In this study, the underpinning theory used to conceptualize blockchain technology is the dynamic capability theory.

2.1.1. Dynamic capability theory

Blockchain technology configures the supply chain resources and enables the members to co-create value by executing assigned tasks with increased transparency and speed (Perks et al., 2017). In this study, we conceptualize blockchain technology using the dynamic capability theory (Teece et al., 1997). Teece et al., p.516) define dynamic capability as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments." Dynamic capability enhances the firm's ability to make decisions, solve problems, identify opportunities and threats, and modify existing resources (Eisenhardt and Martin, 2000). The dynamic capability theory suggests that organizations can create 'value' by modifying supply chain processes and resources. Increased supply chain transparency, immutability, privacy, reliability, and trustworthiness are the principal drivers of blockchain technology (Kamble et al., 2019). These blockchain technology capabilities are expected to provide a competitive advantage in terms of reduced transaction-based costs, the addition of new products and services, delineating the organizational boundaries, automation, and decentralization of supply chain decision making (Angelis and da Silva, 2019; Pereira et al., 2019).

2.2. Blockchain technology adoption

The literature on blockchain suggests various drivers of blockchain adoption that includes a secured and decentralized database, anonymity of transactions, use of smart contracts, reduced transaction costs, and product traceability. Although the blockchain adoption drivers provide various benefits, blockchain adoption within supply chains is still in its infancy stage (Angelis and da Silva, 2019; Queiroz and Fosso Wamba, 2019). Some barriers exist to the successful implementation of blockchain technology adoption. These include issues related to lack of successful validations (Leung, 2016), integration challenges with existing legacy systems (Mougayar, 2017; Earls, 2016), scalability (Eyal et al., 2016), lack of computing power (Bentov et al., 2016), and regulatory and legal governance systems (Duhaime, 2014). Blockchain adoption is expected to bring significant improvements to all business processes for all supply chain participants.

The extant literature details various technology adoption frameworks aiming to analyze users' adoption behavior including the Technology Acceptance Model (TAM) (Davis, 1989), Theory of Planned Behavior (TPB) (Ajzen, 1987), and UTAT (Venkatesh et al., 2012). Previous studies have referred to these frameworks in combination to develop more profound insights on adoption behaviors such as the UTAT framework by Queiroz and Fosso Wamba (2019). It was used to estimate the blockchain adoption behavior between supply chain professionals in India and the USA. The integrated TAM, TPB framework by Kamble et al. (2019) was used to analyze the blockchain adoption behavior of supply chain professionals in India. However, the existing blockchain adoption studies focus on analyzing the individual's intent to adopt the blockchain rather than an organizational perspective. Additionally, the literature suggests that blockchain adoption faces numerous challenges, such as compatibility issues with the existing system, complexity of the supply chain, high implementation costs, and availability of skilled technical human resources (Wang et al., 2018). Therefore, it becomes necessary that blockchain adoption models analyze these factors from an institutional perspective to identify significant factors that lead to supply chain blockchain adoption.

Additional studies are required to develop a comprehensive understanding of blockchain adoption process drivers. A review of recent studies analyzing the adoption behavior of information technology products reveals a clear focus on integrating different adoption models to come up with a more comprehensive understanding of customers' intent to adopt the technology (Kamble et al., 2019; Queiroz and Fosso Wamba, 2019). Therefore, in this study, we use a combination of the TAM and Technology-Organization-Environment (TOE) framework to conceptualize the blockchain adoption model.

2.2.1. Technology acceptance model

The primary objective of the present study is to understand the behavioral process of blockchain adoption within organizations. Many organizations are already implementing the Internet of Things and big data technologies. Should these organizations be moving forward on blockchain adoption? It is essential to understand how these organizations perceive blockchain technology in terms of usefulness and ease of use. Accepting the blockchain will, in turn, expedite their adoption process. Therefore, we have used the perceived usefulness and ease of use as two primary attributes of the adoption process, which is represented by the TAM model (Davis, 1989; Pattansheti et al., 2016).

2.2.2. Technology, organization and environment framework

The TOE framework considers factors under the dimension of technology, organization, and environment, which influence the adoption of innovative technology at the institutional level (DePietro et al., 1990). The technology dimension considers the influence of technical characteristics such as infrastructure, quality, and integration on technology adoption. The organizational aspect of technology adoption include factors such as organizational structure, decision-making capabilities, and management support. Factors related to the influence external parties have on adoption - such as government regulations, supplier support, competitive pressure - are included in the environmental dimension. The TOE is found to be the most robust and widely used adoption model in the information systems literature compared to TAM, TRA, TPB, and IDT, which are focused on analyzing the technology adoption behavior at the individual user's level rather than at the organizational level (Gangwar et al., 2015; Awa et al., 2016). Hence, we conceptualize our research framework on the integration of the TAM and TOE framework. The proposed combination addresses the need for more research on blockchain adoption from both individual and institutional perspectives.

2.3. Bayesian network analysis

The Bayesian network analysis follows the 'Bayes Theorem' by representing causal dependencies of events in a probabilistic network using conditional probabilities (Castillo et al., 1997). The nodes of the probabilistic network represent uncertain variables whereas, the edges of the network represent the causal relationships between two nodes, forming an acyclic directed graph. The node with a parent is referred to as a leaf node, and the node without a parent is called a root node (Aguilera et al., 2011). Compared to other graphical methods such as social network analysis and interpretive structural modeling, the Bayesian network analysis captures the power of relationships between nodes. Therefore, Bayesian network analysis can be used for testing hypotheses (Qazi et al., 2018). Moreover, the Bayesian network analysis offers the advantage of combining multiple information sources, structural learning possibilities, and efficiently dealing with uncertainty (Minana et al., 2012). Furthermore, the Bayesian network analysis offers a high level of flexibility in updating the conditional probabilities, incorporating expert knowledge, and changing the nodes based on suggestion or need (Gupta and Kim, 2008).

The artificial neural network is the other widely used machine learning technique that identifies the non-compensatory and non-linear relationships in the research models (Leong et al., 2015). The literature supports the use of the artificial neural network in producing more accurate predictions compared to the traditional regression-based techniques (Chiang et al., 2006; Leong et al., 2013). The artificial neural networks are known to use a "hill-climbing" approach to learning from the data and are found to be useful in analyzing complex problems when little prior knowledge of the input variables is known, and internal system operation is available (Schalkoff, 1992). However, artificial neural networks fail to provide the reasoning process to human understanding, and the decision-makers cannot be specific on what the artificial neural network has learned (Diederich, 1992). The decision-maker faces difficulty act on an outcome without knowing how the result has arrived (Teach and Shortliffe, 1981). Also, the robustness of the artificial neural network-based models may be significantly deteriorated due to the possible overfitting of data.

Recently, Wong et al. (2019) used an artificial neural network-based methodology to analyze blockchain adoption in supply chains based on the TOE framework. As compared to the artificial neural network, the Bayesian network analysis provide detailed reasoning in the form of probabilities for the obtained results and avoids the risk of overfitting the data (Mitchell, 1997). The literature suggests that the Bayesian network analysis might outperform the artificial neural networks in small data settings. Artificial neural networks, especially the ones with more layers, are very well known to be data-hungry demanding massive datasets to train them properly (Correa et al., 2009).

As the present study aims to understand the blockchain adoption behavior in supply chains, practitioners need to understand the reasoning behind the causal relationships rather than a mere association of data and assumptions. Therefore, we feel that the present study will contribute in terms of extending the work carried by Wong et al. (2019) by deploying an integrated TAM-TOE framework using a Bayesian network methodology to overcome the limitations of the artificial neural network.

3. Research framework

Blockchain adoption is a complex process as it is not only dependent on adequate infrastructure; it also requires addressing integration challenges with existing legacy systems. Blockchain must adhere to the legal and regulatory governance systems. Perceived usefulness is found to be an important mediating variable influencing the relationship between the perceived ease of use and intention to adopt blockchain in the supply chain (Kamble et al., 2019). The literature suggests that the predictive power of a TOE model can be extensively improved by integrating it with other models, as the constructs of the TOE model are too generic and unclear (Wang et al., 2010; Gangwar et al., 2015). These reasons have motivated researchers to use an integrated TAM-TOE framework to assess blockchain technology adoption behavior of users. The constructs selected in the present study and the relationships emerging from the literature form the basis of our hypothesis development and the proposed conceptual framework. Understanding blockchain adoption within supply chains may be of great strategic value to decision-makers to plan their adoption process. This will not only help supply chain practitioners, but also provide meaningful insights to both vendors and strategic partners.

3.1. Technological factors

Various technological factors are hypothesized to influence blockchain technology adoption, including; relative advantage, information security, technical know-how, perceived financial costs, compatibility, and complexity. We will explain these below.

3.1.1. Relative advantage

Relative advantage is defined as "the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 1995, p. 219). The relative advantage increases the probability of innovative technologies adoption (Gangwar et al., 2015). The Blockchain offers the highest level of product traceability and provenance with the use of trusted information as compared to the other technologies (Wang et al., 2018). Previous studies have shown that relative advantage is positively related to the perceived ease of use and perceived usefulness (Davis 1989; DePietro et al., 1990; Gangwar et al., 2015).

Therefore, we hypothesize that:

H1a. Relative advantage positively influences the perceived ease of use.

H1b. Relative advantage positively influences perceived usefulness.

3.1.2. Information security

Information security is defined as "the ability to protect stakeholder's information and their transaction data during transmission" (Hua, 2009). Blockchain technology offers a high level of IS through unique features such as a secured database (Huckle et al., 2016) and a privacy-preserving framework (Ouaddah et al., 2017). Blockchain technology offers users the opportunity to not revealing their identity while performing transactions. However, when blockchain is used within a supply chain, the technology requires user information to be shared with their partners, and hence the information is available for scrutiny. The literature identifies information security threats to influence the adoption of technology (Limthongchai and Speece, 2003; Belkhamza and Wafa, 2009). The user becomes more hesitant to share information because of information security issues, thereby affecting their perceived ease of use and perceived usefulness (Khan and Salah, 2017; Al-Saqaf and Seidler, 2017). Information security is posited to directly influence the user's perceived ease of use and perceived usefulness of the technology (Al-Omari et al., 2012).

Therefore, we hypothesize that:

H2a. Information security positively influences the perceived ease of use.

H2b. Information security positively influences perceived usefulness.

3.1.3. Technical know-how

Technical know-how refers to the organization's ability in terms of the availability of technically skilled experts and consultants to guide blockchain implementation and operations (Eze et al., 2013). Lack of awareness and absence of technical know-how is found to hinder the blockchain adoption, as it is difficult for an organization to adopt something which is not entirely understood (White, 2017). The availability of technical know-how drives the perceived usefulness of the technology. The user's technical knowledge in using the technology reduces the complexities making it effortless (Davis, 1989; Lu et al., 2003).

Therefore, we hypothesize that:

H3a. Technical know-how positively influences the perceived ease of use.

H3b. Technical know-how positively influences the perceived usefulness.

3.1.4. Perceived financial benefits

Perceived financial benefit refers to the implementation and operational costs of the technology and the monetary benefit derived from it (Lee et al., 2012). Blockchain features such as a decentralized and shared database reduce the number of intermediaries resulting in reduced transaction costs (Iansiti and Lakhani, 2017; Kshetri, 2017). Third-party intermediaries are no longer required in a blockchain-based system, and the transactions can be initiated and carried from peer to peer. The organizations realize cost benefits and improved flexibility, as many manual tasks can be automatically executed through smart contracts (Kamble et al., 2019). Compared to traditional supply chains, blockchain-driven supply chains are reported to have lower overhead costs (Sikorski et al., 2017). Perceived financial benefits are related to the perceived ease of use and perceived usefulness of new technologies. That is, customers' perceived financial benefit influences judgment of the usefulness of a technology. If the perceived financial benefit is high, then the user perceives the technology as very useful (Lee et al., 2012).

Therefore, we hypothesize that:

H4a. Perceived financial benefits positively influence the perceived ease of use.

H4b. Perceived financial benefits positively influence perceived usefulness.

3.1.5. Compatibility

Compatibility is defined as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 1995, p.38, 39). Blockchain platforms are based on specific distributed ledger technology that is characterized by different governance structures (de Filippi and Mcmullen, 2018). While selecting the distributed ledger technology during blockchain implementation, companies should check whether they are compatible with various supported financial services and products and meet regulatory requirements. The part of governance structure evolution is complicated, with a wide variety of blockchain applications based on different platforms. Further, there are various features and protocols for the open-source public and private blockchain with potentially different applications (Mthethwa, 2016). The previous studies suggest that a high level of compatibility of the new technology with existing systems will influence the perceived ease of use and perceived usefulness (Calisir et al., 2009; Gangwar et al., 2015).

Therefore, we hypothesize that:

H5a. Compatibility positively influences the perceived ease of use.

H5b. Compatibility positively influences perceived usefulness.

3.1.6. Complexity

Complexity refers to "the perceived difficulty of learning to use and understand a new system or technology" (Sonnenwald et al., 2001, p.115). The significant sources of complexity in a blockchain system are scalability (Eyal et al., 2016), selfish mining (Khan and Salah, 2017), and lack of computing power (Bentov et al., 2016). Scalability refers to the very high velocity of data generation with an increasing number of transactions making the blockchain heavy. The previous literature on perceived complexity claims that a high level of complexity influences the perceived ease of use and perceived usefulness (Gangwar et al., 2015; Parveen and Sulaiman, 2008).

Therefore, we hypothesize that:

H6a. Complexity negatively influences the perceived ease of use.

H6b. Complexity negatively influences perceived usefulness.

3.2. Organizational factors

3.2.1. Organizational readiness

Organizational readiness measures the manager's perception of his organization's competency to adopt the technology based on the judgment of various criteria such as awareness, resources, commitment, and governance (Tan et al. 2007). This criterion is mainly focused on financial readiness (Musawa and Wahab, 2012; Oliveira and Martins, 2010). A high level of organizational readiness positively influences the perceived use of technology (Gangwar et al., 2015). Therefore, we hypothesize the following:

H7. Organisational readiness positively influences perceived usefulness.

3.2.2. Top management support

Raghunathan and Raghunathan (1988) explain top management support as the degree to which top management understands the strategic importance of information system function and is involved in information system activities. Top management support provides a compelling vision to help an organization to overcome any barrier and create an environment of commitment and innovation (Wang et al., 2010). Top management support is found to influence the perceived ease of use and perceived usefulness (Gangwar et al., 2015).

Therefore, we hypothesize the following:

H8a. Top management support positively influences the perceived ease of use.

H8b. Top management support positively influences perceived usefulness.

3.2.3. Training and education

The adoption of any new technology is hindered due to the non-availability of skilled human resources (Kamble et al., 2018). The shortage of technically skilled workforce to implement and operate blockchain technology has directed many organizations to create a talent pool by hiring and training people (Rizzo, 2016). Proper training and education will help the employees to use the technology better and acknowledge the perceived usefulness (White 2017; Kamble et al., 2019).

Therefore, we hypothesize that;

H9a. Training & education positively influence the perceived ease of use.

H9b. Training & education positively influence perceived usefulness.

3.3. Environmental factors

3.3.1. Partner readiness

The successful implementation of the blockchain depends on the level of supply chain integration achieved with existing supply chain partners (Queiroz and Fosso Wamba, 2019). The partners' willingness and cooperation to be part of the blockchain initiative is a highly critical element of implementation and is not possible with flawed relationships between them (Mougayar 2017; Earls, 2016). The literature indicates that an organization that adopts an innovation would expect their partners to possess a similar innovation process to fully utilize the innovation at an inter-organizational level (Hameed and Counsell, 2012). We assume that the partner readiness level will have a positive influence on blockchain technology.

Therefore, we hypothesize that:

H10. Partner readiness has a positive influence on blockchain adoption.

3.3.2. Competitive pressure

Competitive pressure refers to the degree of pressure that a company feels from competitors within the industry (Zhu and Kraemer, 2005). Modern technologies provide leverage to supply chains to achieve a competitive advantage over competitors. Blockchain technology offers an opportunity for supply chains to create various sharing applications such as peer-to-peer automatic payment mechanisms, foreign exchange platforms, digital rights management, and cultural heritage (Huckle et al., 2016). Most companies would like to reap such benefits in the ever-increasing competitive market (Haoyan et al., 2017). By adoption of information systems, the organizations might be able to alter rules of the competition and leverage new ways to outperform their competitors, thereby changing the competitive structure in the industry (Porter and Millar, 1985). It is assumed that the organizations adopting blockchain technology will gain competitive advantages over their competitors.

Therefore we hypothesize that;

H11. CP has a positive influence on the blockchain adoption.

3.4. TAM factors

The intention to adopt blockchain technology is influenced by perceived ease of use and perceived usefulness. Perceived usefulness measures the extent to which the prospective user perceives the blockchain adoption will increase the organizational performance (Davis, 1989).

3.4.1. Perceived usefulness and perceived ease of use

TAM proposes that the constructs perceived usefulness, perceived ease of use, and the technology adoption are related (Davis, 1989). The perceived ease of use positively influences the perceived usefulness because technologies requiring fewer efforts can be more useful (Kamble et al., 2019; Gangwar et al., 2015). Several research studies have identified the perceived ease of use and perceived usefulness as primary predictors of technology adoption (Davis, 1989; Venkatesh and Morris 2000). We assume these behavioral relationships would be applicable in blockchain technology adoption.

Therefore we hypothesize that;

H12. Perceived ease of use positively influences the perceived usefulness.

H13. Perceived ease of use positively influences blockchain adoption.

H14. Perceived usefulness positively influences the blockchain adoption.

The research framework based on the above hypothesis is presented in Fig. 1.

4. Research design

The study used primary survey data from Indian manufacturing firms. Collected data were tested for statistical validity before using SEM and Bayesian network analysis.

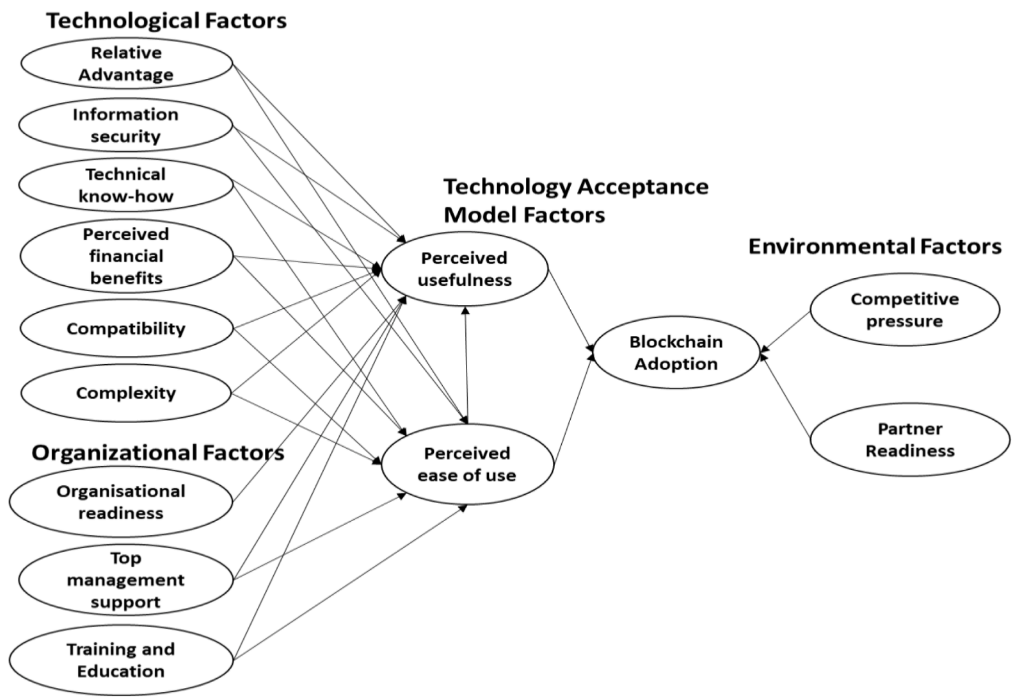

Fig. 1. Research Framework.

4.1. Survey instrument

The measurement scales for the constructs used in the study were developed from the existing studies in the literature (Gangwar et al., 2015; Kamble et al., 2019; Awa et al., 2016). The selected scales were modified to suit the present context of blockchain adoption in manufacturing supply chains. The modifications were based on a consultation process with both industry and academic experts. The expert panel included a total of twenty-five members, including nine senior supply chain executives, five senior system integrators, five senior consultants working in the domain of IT applications in supply chains, three academicians from computer science engineering, three from supply chain management. Experts also suggested changes in the grammar, wording, sequencing, and language based on their understanding of the scales and what these scales intended to measure. These suggestions have ensured the construct validity of the survey instrument used for the study. The final measurement scale used for this study is given in table 2.

4.2. Survey design and sample

As the blockchain adoption is done at the organizational level, the unit of analysis is chosen as an individual manufacturing firm. The blockchain is expected to facilitate internal and external supply chain integration using a single platform. The decision related to blockchain adoption is at the organizational level, and hence we assume that using individual manufacturing firms as the unit of analysis was appropriate. Data for the study were collected from two significant industrial clusters in India, namely: Mumbai-Pune and Bangalore –Chennai. Participating companies belong to the automobile, chemical, and pharmaceutical industries. Mumbai and Bangalore are the renowned pharmaceutical and chemical manufacturing hubs. Pune has more than 750 large and medium-sized automobile component manufacturing companies (Pugaokar, 2015); and Chennai is the country's largest automotive exporter (Menon, 2010) and Mumbai. The online survey questionnaire was sent to 650 respondents representing 300 companies (on average, two respondents from each company). The respondents have participated in the survey voluntarily, and follow-up reminders were sent at regular intervals. Overall, completed responses were received from 289 respondents (success rate: 44.46%), representing 181 companies (success rate: 60%). On average, 1.60 respondents participated in the survey. The survey responses for each company were averaged to obtain a single response for each company (Venkatraman and Grant, 1986). Hence, all statistical analysis was performed on an adequate sample size of 181 manufacturing organizations. Previous studies investigating the predictive behavioral networks based on technology adoption frameworks using machine learning algorithms such as artificial neural network and principal component analysis have used similar sample sizes (such as Wong et al., 2019; Kalinić et al., 2019; Tan et al., 2014; Liébana-Cabanillas et al., 2018). Compared to artificial neural networks, Bayesian network analysis is evaluated based on conditional probabilities, performs well in small data settings, and does not require considerable datasets to train them, suggesting that the adequacy of selected sample size (Mitchell, 1997; Correa et al., 2009). Further, The sample size of 181 manufacturing units was found to be enough to perform the Confirmatory Factor Analysis (CFA) and SEM considering resource constraints in collecting pieces of information and emerging topic such as blockchain adoption in supply chains (Wolf et al., 2013; Sideridis et al., 2014; Hair et al., 2014). The power analysis (1-β) was computed to test the appropriateness of the sample size (Cohen, 1992). The post-doc analysis performed on G*Power 3.1.9.7 for a sample size of 181 at a significance level of 0.05 and an effect size of 0.10 resulted in the power of 0.99, which is above the recommended cut-off of 0.80 (Cohen, 1992).

The demographic details of the selected sample are shown in Table 1.

The online survey methodology adopted for this study has eliminated the issue of missing values and incomplete questionnaires, given the final submission of the online form was allowed only after filling responses to all questions. However, any influence of time lag that was observed, leading to early and the submissions of questionnaires was evaluated, treating them as non-response bias (Oppenheim, 1966). Out of the 289 questionnaires, 105 were received in the first six weeks, 45 were received between week six to week ten, and the remaining 31 questionnaires after ten weeks. The total duration of the study was fifteen weeks, starting from 10th October 2018.

Table 1
Sample characteristics.

Parameter		Number (%)
Industry type	Automobile	82 (45%)
	Chemical	54 (30%)
	Pharmaceutical	45 (25%)
Number of employees	Less than 100 employees	32 (18%)
	100–500 employees	72 (39%)
	500–1000 employees	56 (31%)
	Above 1000 employees	21 (11%)
Ownership	Private	98 (54%)
	Private- listed	51 (28%)
	Joint venture	32 (18%)
Product form	Raw material	42 (23%)
	Components	40 (22%)
	Finished products	99 (55%)
Job domain*	Plant head	20 (7%)
	Operations	58 (20%)
	Supply chain planning	121 (42%)
	Logistics	49 (17%)
	Procurement	41 (14%)
Job position*	Junior management (e.g., Junior system analysts, Integration executive, supply chain planner, junior procurement Officer, Assistant Manager, Manager)	122 (42%)
	Middle management (e.g., Sr. Manager, Sr. Executive, Head of Department)	105 (36%)
	Senior Management or Director	62 (22%)
Age*	Less 26 – 35 years	105 (36%)
	Between 36- - 45 years	110 (38%)
	Between 46 – 55 years	52 (18%)
	Above 55 years	22(08%)
Work experience*	Between 1–5 years	81 (28%)
	Between 6–10 years	113 (39%)
	Between 11- 15 years	55 (19%)
	15 years and above	40 (14%)

* the sample size included a total of 289 respondents representing 181 organizations.

4.3. Methods

A two-stage integrated research methodology was used to develop the behavioral predictive blockchain adoption model. The stage-I of the research was focused on validating the measurement items used for the study and testing the statistical significance of the proposed structural framework, as shown in Fig. 1. In stage-II, Bayes network methodology was applied to the validated structural model to develop a predictive blockchain adoption model. The research methods used in these two stages are discussed below.

4.3.1. Convergent and discriminant validity test

The validity of the collected data was performed to test the presence of non-response bias, common method bias, and normality of the data. One-way Analysis of Variance (ANOVA) was used to analyze the presence of non-response bias. The difference in the means of three groups created on time lags in the submission of completed questionnaires was used as the basis for comparison. The presence of common method bias (CMB) was tested using Harman's single factor score as per the guidelines suggested by Podsakoff and Organ (1986). The normality of the data was ascertained using the Kurtosis and Skewness values (Curran et al., 1996). The convergent and discriminant validity of the measurement items was confirmed through the values of factor loadings, composite scale reliability (CSR), and average variance extracted (AVE). The convergent validity was confirmed on satisfying the following threshold values; factor loadings greater than 0.5 (Hair et al., 2014), CSR values above 0.70 (Hair et al., 2014; Gefen et al., 2000), and the average variance extracted (AVE) values above 0.50 (Hair et al., 2014; Fornell and Larcker, 1981). The Chi-square value (χ^2), degree of freedom (df), Comparative Fit Index (CFI), Tucker-Lewis index (TLI), and Root Mean Square Error of Approximation (RMSEA) were used to test the hypothesized measurement model (Fan et al., 2016; Hu and Bentler, 1999).

4.3.2. Structural equation modelling

The proposed structural model, as shown in Fig. 1 was analyzed using the maximum likelihood estimation method in AMOS 24. The SEMs models estimate the cause and effect relationships between a set of multivariate data. SEM uses latent variables to model the classical measurement error model for predictors and random-effects model for multivariate outcomes (Sanchez et al., 2005). The SEM technique involves two main phases. In phase I, the factors defining the latent variables are validated (as explained in Section 4.3.2). Phase II evaluates the model fit of the structural model to test the statistical relevance of the model (Jenatabadi, 2015). However, the SEM has limited utility for managers due to the inability to act as a decision support system that can be used for further diagnosis and prediction of the dependent variables (Gupta and Kim, 2008).

4.3.3. Bayesian network

In this stage, we adopted a Bayesian network analysis for developing and validating our proposed predictive blockchain adoption model (Gupta and Kim, 2008). The development of a structural model, on the one hand, and estimating prior conditional probabilities, on the other hand, are the two critical steps in developing a Bayesian network (Heckerman, 1999).

The latent variable scores of the significant constructs in the structural model were estimated and used as the data for learning the conditional probabilities. The use of latent scores ensured that the two modeling approaches did not differ much due to the lack of factor determinacy (Steiger, 1996). The latent scores were calculated as per guidelines suggested by Joreskog (2000) using AMOS software. Latent variable scores support the testing of non-linear relationships between the latent variables (Joreskog, 2000). The latent variable scores are best suited to test the Bayesian networks in their functional form and represent non-linear relationships.

In SEM, the measurement model for exogenous variables is given as, $x = A_x\xi + \delta$ where, x is the individual items for independent variables, ξ is the latent variable corresponding to the item x, A_x is the standardized coefficient of relationship between x and ξ. The measurement error term x is represented by δ.

The latent scores ξ for each observation in the sample are calculated based on the estimation of the coefficients by minimizing the equation $\sum_{i=1}^{N}(x_i - A_x\xi_i)\mathrm{T}\theta_\delta^{-1}(x_i - A_x\xi_i)$, Subject to the constraint: (1/N) $\sum_{i=1}^{N}\xi_i\xi_i^T = \varphi$.

Where N is the sample size, θ_δ is the covariance matrix of residual errors, Φ is the covariance matrix of the latent variables, and the transpose of the computed matrix is represented by T.

The significant latent constructs in the model were first discretized into two categories (low and high), and the probabilities were manually estimated by occurrence frequency. The two-category discretization (low and high) was performed in Rapidminer Studio 8.0, using the Discretize by Binning operator. This operator discretizes the selected numerical attributes to nominal attributes. The *number of bins* parameter is used to specify the required number of bins. This discretization was performed by simple binning. The range of numerical values is partitioned into segments of equal size.

5. Analysis and findings

5.1. Measurement model

The ANOVA test revealed no significant differences in the mean values on the selected constructs across the three groups established on the questionnaire submission timeline indicating the absence of non-response bias. The Harmon's single factor test to test the common method bias revealed that the maximum amount of variance explained by a single factor was 41.2%, which implies that the common method bias was not a significant issue in this study. The absolute values for Skewness and Kurtosis were within the threshold limits of 2 and 7, suggesting the data was normal (Curran et al., 1996; Ryu, 2011). The mean values, standard deviation, Skewness, and Kurtosis values are shown in Table 2.

To test the reliability and validity of the measurement items, various measures that included exploratory factor analysis, Composite Scale Reliability (CSR), Average Variance Extracted (AVE) were used. As shown in Table 2, factor loading values for the measurement items were higher than the threshold of 0.50 (Hair et al., 2014). The CSR values were also found to be above the threshold of 0.70 establishing adequate internal consistency of the measurement items (Gefen et al., 2000). AVE values for all constructs were higher than the threshold of 0.5, except for the construct organizational readiness signifying convergent validity issue (Hair et al., 2014). In table 3, we have compared the correlation coefficients between constructs with the diagonal elements of the matrix representing the squared roots of the construct's AVE. The comparison reveals that correlation coefficients of one construct with the other construct are lower than the squared roots of the construct's AVE, signifying no discriminant validity issues except for the construct organizational readiness (Hair et al., 2014). The construct organizational readiness was dropped from further analysis due to the biasness of the respondents.

The Confirmatory Factor Analysis (CFA) of the measurement model suggested a satisfactory fit with the values for model fit indices of $\chi2/df$ =1.679 (2017.76/1233), RMSEA=0.061, CFI=0.936, and TLI=0.929 (Fan et al., 2016; Hu and Bentler, 1999). Next, the model was tested for estimating the hypothesized relationships. The results of the SEM analysis are summarized in table 4.

5.2. SEM results

The proposed structural model, as shown in Fig. 1 was analyzed using the maximum likelihood estimation method in AMOS 24. The estimates of the validated SEM model and the results of the hypothesis are summarized and shown in table 4.

In this stage, we tested the hypothesis that was developed based on the theoretical foundations in the literature. All the hypotheses were examined using the SEM approach. The results found that information security was an insignificant variable and had no influence on the perceived ease of use and the perceived usefulness (H2a and H2a). The finding was inconsistent with the existing literature (Awa et al., 2016; Gangwar et al., 2015; Belkhamza and Wafa, 2009). This may be because the supply chain practitioners know the primary value offered by blockchain technology is transparent transactions, the anonymity of transactions, smart contracts, and product traceability. The relative advantage was found to have a significant relationship with the perceived usefulness (H2b), which found support in the literature (Kamble et al., 2019; Gangwar et al., 2015; Musawa and Wahab, 2012). However, the influence of relative advantage on perceived ease of use (H1b) deviated from the findings in the literature showing an insignificant relationship. This implies that the practitioners perceive that the benefits offered by blockchain adoption will make their existing processes more efficient. The organizations tend to perceive blockchain's usefulness when they find that it provides them a relative advantage over the existing applications. However, they perceive it will not be easy to use this technology compared to the current systems.

The technical know-how was found to have a significant influence on the perceived ease of use (H3a). The survey respondents in our study had a technical background and were eager to learn and adopt blockchain technology in their organizations (Wong et al., 2020; Kamble et al., 2019; Queiroz and Fosso Wamba et al., 2019). The organizations believed that the perceived financial benefits that will be accrued from blockchain adoption would influence the perceived ease of use (H4a)

Table 2
Descriptive statistics and normality test results.

Variables	Mean scores	Std. Deviation	Skewness	Kurtosis	Factor loadings
Technological Factors					
Relative advantage (RA)					
Blockchain will scale up our operations better (RA1)	3.51	0.76	-0.55	1.31	.890
Blockchain will provide access to remote information from any time from any place better (RA2)	3.54	0.76	-0.66	1.54	.868
Blockchain requires less IT infrastructure maintenance (RA3)	3.46	0.81	-0.52	0.68	.880
Blockchain will help us to access shares resources better (RA4)	3.48	0.74	-0.32	1.07	.874
Information Security (IS)					
Supply chain transactions on blockchain are safe (IS1)	3.60	1.25	-0.53	-0.74	.772
Information sharing in blockchain is safe (IS2)	3.45	1.38	-0.46	-0.97	.803
Blockchain provides high level of data security (IS3)	3.40	1.29	-0.39	-0.89	.815
Technical know-how (TKH)					
Availability of technical workforce (TKH1)	3.50	0.75	-0.44	1.19	.830
Access to technical consultants (TKH2)	3.69	0.91	-0.58	0.35	.814
Successful implemented similar technologies in the past (TKH3)	3.73	0.89	-0.71	0.75	.748
Access to the technical vendors and service providers implementing blockchain (TKH4)	3.78	0.92	-0.64	0.45	.826
Perceived financial benefits (PFB)					
Reduction in the operating costs (PFB1)	3.66	0.92	-0.49	0.21	.881
Reduction in the transaction costs (PFB2)	2.18	1.01	1.16	1.28	.870
Add new customers increasing	2.21	0.98	1.20	1.46	.823

(continued on next page)

Table 2 (*continued*)

Variables	Mean scores	Std. Deviation	Skewness	Kurtosis	Factor loadings
profitability (PFB3)					
Retain existing customers increasing profitability (PFB4)	2.28	1.10	1.10	0.74	.838
Compatibility (COMPB)					
Compatibility with existing technological architecture (COMPB1)	2.25	1.05	1.01	0.61	.834
Scope for customization (COMPB2)	3.67	0.99	-0.60	0.12	.797
Customization in blockchain applications are easy (COMPB3)	3.60	0.96	-0.56	0.22	.780
Compatibility with the existing formats, process interfaces and data (COMPB4)	3.60	1.04	-0.52	-0.28	.740
Complexity (COMPX)					
It is not flexible to interact with blockchain applications (COMPX1)	2.58	0.64	-0.88	0.23	.870
BT create vulnerability of computer breakdowns and loss of data (COMPX2)	2.66	0.71	-0.36	0.06	.827
Its difficult for blockchain to integrate complex supply chain operations (COMPX3)	2.70	0.82	0.49	1.67	.791
Blockchain is going to be time consuming (COMPX4)	2.67	0.69	-0.68	0.42	.711
Organizational Factors					
Organizational Readiness (OR)					
Access to technical knowledge to implement blockchain (OR1)	1.84	0.75	1.14	1.90	.630
Access to computers to implement blockchain (OR2)	1.75	0.70	1.18	2.56	.670
Access to internet connectivity to implement blockchain (OR3)	1.82	0.80	1.24	1.75	.699
Availability of funds to implement blockchain (OR4)	1.80	0.76	1.26	2.20	.577
Top Management support (TMS)					
Blockchain is seen with strategic importance by our top management (TMS1)	2.69	0.96	-0.38	-0.42	.891
Top management is prepared to take the risks associated with blockchain implementation (TMS2)	2.77	0.87	-0.30	-0.34	.917
Top management promotes the culture of transparency and accountability acquired through information sharing (TMS3)	2.81	0.85	-0.46	-0.01	.901
Top management have exhibited strong leadership and engagement while adopting ICT innovations in the past (TMS4)	2.82	0.94	-0.56	0.05	.816
Training and Education (TE)					
Training imparted on blockchain improves level of understanding on blockchain substantially (TE1)	2.61	0.89	-0.02	-0.74	.695
Organization provides complete training on blockchain (TE2)	2.59	0.88	0.03	-0.73	.667
The training programs on blockchain increased confidence (TE3)	2.59	0.87	-0.03	-0.67	.675
Environmental factors					
Competitive pressure (CP)					
Blockchain offers competitive advantages (CP1)	3.64	1.04	-0.61	0.05	.826
Competitors are in the process of implementing blockchain (CP2)	3.49	1.10	-0.34	-0.59	.796
Competitors will become more competitive with blockchain implementation (CP3)	3.60	1.07	-0.52	-0.13	.820
Competitors will have improved	3.54	1.02	-0.40	-0.06	.794

(*continued on next page*)

Table 2 (*continued*)

Variables	Mean scores	Std. Deviation	Skewness	Kurtosis	Factor loadings
processes with blockchain implementation (CP4)					
Competitors will have reduced transaction time and costs with blockchain implementation (CP5)	3.59	1.06	-0.51	-0.12	.815
Partner Readiness (PR)					
Supply chain partners are very enthusiastic about blockchain implementation (TPS1)	3.29	1.22	-0.39	-0.67	.905
Supply chain partners are willing to support blockchain implementation (TPS2)	3.28	1.20	-0.43	-0.61	.907
Supply chain partners are willing to change their processes and practices for blockchain (TPS3).	3.50	1.07	-0.28	-0.52	.901
Supply chain partners have always supported us in the past in implementing ICT initiatives (TPS4)	3.57	1.05	-0.69	0.23	.903
TAM Constructs					
Perceived ease of use (PEOU)					
Blockchain system is easy to understand (PEOU1)	3.46	1.08	-0.28	-0.72	.929
Blockchain is easy to earn (PEOU2)	3.27	1.12	-0.03	-1.04	.831
Blockchain is easy to use (PEOU3)	3.41	1.04	-0.20	-0.57	.919
Blockchain features will be easy compared to other technologies (PEOU4)	3.33	1.13	-0.09	-1.03	.873
Perceived usefulness (PU)					
Blockchain will help improve business efficiency (PU1)	3.81	1.16	-0.83	-0.05	.581
Blockchain will help improve business productivity (PU2)	3.80	1.06	-0.81	0.37	.598
Blockchain will improve the quality of business operations (PU3)	3.79	1.11	-0.80	0.26	.611
Blockchain develops organizational competitiveness (PU4)	3.78	1.05	-0.84	0.49	.550
Blockchain adoption (BA)					
Use of blockchain on a regular basis in future (BA1).	3.83	1.03	-0.82	0.38	.739
Using blockchain is advantageous (BA2).	3.83	1.02	-0.79	0.30	.801
Firm is in favor of using blockchain (BA3)	3.87	1.05	-0.88	0.41	.747

supporting the findings of the other studies (Wong et al., 2020; Iansiti and Lakhani, 2017; Gangwar et al., 2015). The organizations also perceived that the less complex technologies would improve the perceived ease of use, thus leading to increased adoption of the blockchain (H6a). This finding found support in the literature (Wong et al., 2020; Parveen and Sulaiman, 2008; Ramdani et al., 2009; Wang et al., 2010). However, our study reported that the less complex technologies are insignificant in influencing the perceived usefulness deviating from the existing literature (Gangwar et al., 2015; Parveen and Sulaiman, 2008).

The training & education representing the organizational factor was found to have a positive and significant influence on perceived ease of use and perceived usefulness, accepting the hypothesis H9a and H9b. The finding implies that with the increased technical knowledge of the employees on the deployment of blockchain technology, the organizations feel it is easier for them to use blockchain technology in the supply chain and convince them of its utility. The organizations should develop continuous training and education modules on how the blockchain technology can be deployed and its benefits to provide a sense of ease and usefulness in the minds of the employee. The finding found support in the literature and was consistent with HYPERLINK \l "bib133" Wong et al., (2020); White (2017); Kamble et al., (2019), and Awa et al. (2016).

The results confirmed the positive and significant influence of the compatibility on perceived usefulness, establishing the hypothesis H5b, which implies that compatibility of the blockchain with the existing technologies in the organizations will improve its utility. This finding is consistent with the other studies in the literature (Gangwar et al., 2015; Calisir et al., 2009). Further, the perceived ease of use was found to influence the perceived usefulness (H12). The finding implies that the perceived usefulness of the blockchain increases with increased ease of use of the technology. This is consistent with the studies conducted by Davis (1989), Venkatesh and Morris (2000), and Kamble et al., (2019).

Further, both the TAM constructs viz., perceived ease of use, and perceived usefulness were found to have a positive influence on intention to adopt blockchain technology accepting the hypothesis H13 and H14. The findings were supported by the studies in the existing literature (Kamble et al., 2019; Gangwar et al., 2015; Davis, 1989; Venkatesh and Morris, 2000) indicating that the perceived usefulness and perceived ease of use are the significant antecedents to the blockchain adoption. Partner readiness was found to be significant in influencing the blockchain adoption (H10). Blockchain technology needs to be implemented across the supply chain requiring massive support from all the supply chain partners. This finding is supported in the literature by many other studies conducted in different contexts (Queiroz and Fosso

Table 3
Discriminant validity test results.

	CR	AVE	TMS	PEOU	PU	CP	SEC	PR	BA	RA	TKH	PFB	COMPB	COMPX	OR	TE
TMS	0.785	0.563	0.751													
PEOU	0.955	0.841	0.051	0.917												
PU	0.916	0.732	-0.058	0.414	0.855											
CP	0.972	0.897	-0.073	0.291	0.730	0.947										
SEC	0.736	0.512	-0.063	0.013	0.228	0.213	0.695									
PR	0.850	0.613	-0.116	0.218	0.447	0.438	0.140	0.783								
BA	0.904	0.759	-0.101	0.367	0.828	0.705	0.192	0.475	0.871							
RA	0.981	0.929	-0.013	0.280	0.707	0.558	0.088	0.292	0.511	0.964						
TKH	0.976	0.910	-0.039	0.400	0.629	0.474	0.077	0.314	0.585	0.408	0.954					
PFB	0.970	0.891	0.070	-0.268	-0.648	-0.574	-0.168	-0.384	-0.875	-0.378	-0.469	0.944				
COMPB	0.971	0.895	-0.110	0.312	0.720	0.614	0.106	0.424	0.932	0.432	0.561	-0.780	0.946			
COMPX	0.924	0.755	-0.119	0.384	0.472	0.357	0.057	0.233	0.467	0.312	0.536	-0.363	0.388	0.869		
OR	0.717	0.390	-0.207	0.278	0.467	0.389	0.012	0.277	0.464	0.275	0.491	-0.379	0.394	0.927	0.624	
TE	0.980	0.943	-0.022	0.334	0.959	0.650	0.185	0.399	0.743	0.662	0.597	-0.579	0.648	0.402	0.410	0.971

The values in bold are the square root of AVE scores.
RA: Relative advantage, TMS: Top management support, COMPB: Compatibility, TE: Training & Education, PFB: Perceived financial benefits, TKH: Technical know-how, PEOU: Perceived ease of use, PU: Perceived usefulness, OR: Organizational readiness; CP: Competitive pressure, PR: Partner readiness, BA: Blockchain adoption.

Table 4
Summary of SEM results.

Dependent variable	Independent variable	Hypothesis	Standardized estimate	P-value	R^2	Result
Perceived ease of use	Relative advantage	H1a	.039	.392		ns
	Information security	H2a	.085	.061	.630	ns
	Technical know-how	H3a	.536	***		s
	Perceived financial benefit	H4a	-0.139	***		s
	Compatibility	H5a	.049	.277		ns
	Complexity	H6a	.397	***		s
	Top management support	H8a	.014	.762		ns
	Training & education	H9a	.352	***		s
Perceived Usefulness	Relative advantage	H1b	.118	***		s
	Information security	H2b	.052	.114	.807	ns
	Technical know-how	H3b	.006	.897		ns
	Perceived financial benefit	H4b	-0.016	.653		ns
	Compatibility	H5b	.159	***		s
	Complexity	H6b	.016	.681		ns
	Organizational readiness	H7*				
	Top management support	H8b	.144	***		s
	Training & education	H9b	.827	***		s
	Perceived ease of use	H12	.112	.037		s
Blockchain Adoption	Partner readiness	H10	.290	***		s
	Competitive pressure	H11	.359	***		s
	Perceived ease of use	H13	.202	.001		s
	Perceived usefulness	H14	.312	***	0.403	s

**dropped from the study because of convergent validity concerns.*
ns: not supported.
s: supported.

Wamba, 2019; Lin and Lin, 2008; Oliveira and Martins, 2010). Finally, the competitive pressure was found to be one of the most critical factors influencing the blockchain adoption (H11). This finding found support in the literature form other studies (Low et al., 2011; Oliveira and Martins, 2010) but was inconsistent with a few studies (Ramdani et al., 2009). The positive influence of competitive pressure on blockchain technology indicates that blockchain technology is perceived by the organizations as a strategic necessity and critical innovation for survival.

The findings on the TAM and T-O-E factors imply that the blockchain adoption is not only dependent on the usefulness and ease of use of the technology, which is highly influenced by the technological and organizational factors within the control of the organization but is also subjected to externally uncontrollable factors such as competitive pressures and the readiness of the supply chain partners to adopt the technology.

5.2.1. Mediation analysis

The mediation analysis was performed using the user-defined estimands in the software AMOS 24.0 as per the guidelines suggested by Arbuckle (2014) and Hayes and Scharkow(2013). The results revealed that the mediation effects were statistically significant (at 0.05) except for the single level mediation between top management support, perceived usefulness, and blockchain adoption with an estimate of -0.008 and a p-value of 0.417. The finding indicates that the perceived usefulness of blockchain technology may be influenced by the top management support to use blockchain in the organization; however, this may not translate in blockchain adoption by the organization. Therefore, the top management support is limited in developing perceived usefulness (H8b) and does not have an indirect influence on blockchain adoption. The results of the mediation analysis are presented in Table 5.

5.3. Results of the Bayesian network analysis

The observed prior conditional probabilities obtained for the constructs using the steps outlined in Section 4.3.2 are shown in table 6.

Next, the conditional probabilities were estimated based on the prior conditional probabilities and the analysis of the parent-child relationship between variables in the structural model. For example, in our network, the variables perceived ease of use, perceived usefulness,

Table 5
Results of mediation analysis (User-defined estimands).

Paths	Estimate	Lower	Upper	P-value
TKH*PEOU*ADOP	.085	.037	.146	.002
PFC*PEOU*ADOP	-0.028	-0.066	-0.009	.002
COMPX*PEOU*ADOP	.087	.038	.173	.001
TRAIN*PEOU*ADOP	.057	.025	.109	.001
RA*PU*ADOP	.034	.008	.070	.026
COMPTAB*PU*ADOP	.036	.010	.075	.010
TM*PU*ADOP	-0.008	-0.035	.010	.417
TRAIN*PU*ADOP	.207	.098	.309	.002
PEOU*PU*ADOP	.035	.009	.081	.023
TKH*PEOU*PU*ADOP	.015	.003	.037	.024
PFC*PEOU*PU*ADOP	-0.005	-0.014	-0.001	.015
COMPTAB* PEOU*PU*ADOP	.015	.005	.035	.015
TRAIN* PEOU*PU*ADOP	.010	.002	.028	.017

RA: Relative advantage, TMS: Top management support, COMPB: Compatibility, TE: Training & Education, PFB: Perceived financial benefits, TKH: Technical know-how, PEOU: Perceived ease of use, PU: Perceived usefulness, OR: Organizational readiness; CP: Competitive pressure, PR: Partner readiness, BA: Blockchain adoption.

competitive pressure, Partner readiness are the parents to the variable blockchain adoption (child). In this case, the conditional probability for the variable blockchain adoption is derived from the discrete values of perceived ease of use, perceived usefulness, competitive pressure, and Partner readiness, i.e., *P (Blockchain adoption | Perceived ease of use, Perceived usefulness, Competitive pressure, Partner readiness)*. Similarly, the conditional probability for perceived ease of use is estimated as *P (Perceived ease of use | Training & education, Perceived financial benefits, Complexity, Technical know-how)*. The conditional probabilities for the two states (low and high) at the child nodes are shown in table 7 for perceived ease of use, perceived usefulness, and blockchain adoption. Bayesian network analysis uses Markov conditions (Hausman and Woodward, 1999). The joint probability over all the variables in the Bayes network is calculated as;

$$P(Z_1 = z_1, \ \ldots\ldots, \ Z_n = z_n) = \prod_{i=1}^{n} P\ (Z_i | Parents(Z_i))$$

As applied to our model, "Z_1" is the variable, and "z_1" is a state of it being "high" or "low." The right-hand side of the equation represents the product of all the conditional probabilities. The term "Parents (Zi)" in the equation represents all the parent nodes of the child variable "Zi." Therefore, the joint probability in our model is P(Relative advantage,

Table 6
Prior conditional probabilities of the constructs.

State of event	RA	TMS	COMPB	TE	PFB	COMPX	TKH	PEOU	PU	CP	PR	BA
Low	0.625	0.66	0.67	0.86	0.73	0.33	0.26	0.46	0.24	0.2	0.27	0.11
High	0.375	0.34	0.33	0.14	0.27	0.67	0.74	0.54	0.76	0.8	0.73	0.89

RA: Relative advantage, TMS: Top management support, COMPB: Compatibility, TE: Training & Education, PFB: Perceived financial benefits, TKH: Technical know-how, PEOU: Perceived ease of use, PU: Perceived usefulness, CP: Competitive pressure, PR: Partner readiness, BA: Blockchain adoption.

Table 7
Conditional probabilities for perceived ease of use, perceived usefulness, and blockchain adoption.

PEOU	RA	COMPB	TMS	TE	PU		TKH	PFB	COMPX	TE	PEOU		PEOU	PU	CP	PR	BA	
					L	H					L	H					L	H
L	L	L	L	L	0.33	0.66	L	L	L	L	1	0	L	L	L	L	1	0
L	L	L	L	H	0	1	L	L	L	H	1	0	L	L	L	H	0.5	0.5
L	L	L	H	L	0.66	0.33	L	L	H	L	0.5	0.5	L	L	H	L	0.5	0.5
L	L	L	H	H	0.33	0.66	L	L	H	H	0.8	0.2	L	L	H	H	0.06	0.94
L	L	H	L	L	0	1	L	H	L	L	0.9	0.1	L	H	L	L	0	1
L	L	H	L	H	1	0	L	H	L	H	0.75	0.25	L	H	L	H	0	1
L	L	H	H	L	0.6	0.4	L	L	H	L	0.5	0.5	L	H	H	L	0.13	0.87
L	L	H	H	H	0.33	0.66	L	H	H	H	0.42	0.58	L	H	H	H	0.07	0.93
L	H	L	L	L	0.5	0.5	H	L	L	L	0.5	0.5	H	L	L	L	1	0
L	H	L	L	H	0.25	0.75	H	L	L	H	0.25	0.75	H	L	L	H	0	1
L	H	L	H	L	0.45	0.55	H	L	H	L	0.6	0.4	H	L	H	L	0	1
L	H	L	H	H	0.25	0.75	H	L	H	H	0	1	H	L	H	H	0	1
L	H	H	L	L	0	1	H	H	L	L	0.57	0.43	H	H	L	L	0	1
L	H	H	L	H	0	1	H	H	L	H	0.7	0.3	H	H	L	H	0.15	0.85
L	H	H	H	L	0.35	0.65	H	H	H	L	0.24	0.76	H	H	H	L	0.105	0.895
L	H	H	H	H	0	1	H	H	H	H	0.36	0.64	H	H	H	H	0.03	0.97
H	L	L	L	L	0.5	0.5												
H	L	L	L	H	0	1												
H	L	L	H	L	0.33	0.66												
H	L	L	H	H	0	1												
H	L	H	L	L	0.5	0.5												
H	L	H	L	H	0	1												
H	L	H	H	L	0.5	0.5												
H	L	H	H	H	0	1												
H	H	L	L	L	0.25	0.75												
H	H	L	L	H	0	1												
H	H	L	H	L	0.53	0.47												
H	H	L	H	H	0	1												
H	H	H	L	L	0.2	0.80												
H	H	H	L	H	0	1												
H	H	H	H	L	0.07	0.93												
H	H	H	H	H	0	1												

RA: Relative advantage, TMS: Top management support, COMPB: Compatibility, TE: Training & Education, PFB: Perceived financial benefits, TKH: Technical know-how, PEOU: Perceived ease of use, PU: Perceived usefulness, CP: Competitive pressure, PR: Partner readiness, BA: Blockchain adoption.

Top management support, Compatabilty, Complexity, Perceived financial benefit, Training & education, Technical know-how, Perceived usefulness, Perceived ease of use, Competitor pressure, Partner readiness, Blockchain adoption) and is calculated as per the conditional probabilities at each node as; P(Relative advantage,…….. blockchain adoption) = *P*(Relative advantage) x P(Top management support) x P (Compatibility) x P(Complexity) x P(Perceived financial benefit) x P (Training & education) x P(Technical know-how) x P(Competitive pressure) x P(Partner readiness) x P(Perceived usefulness |Relative advantage, Top management support, Compatibility, Training & education) x P(Perceived ease of use |Training & education, Perceived financial benefit, Complexity, Technical know-how) x P(blockchain adoption | Perceived ease of use, Perceived usefulness, Competitive pressure, Partner readiness) The organizations may use this model to predict the probability of their blockchain adoption, by assigning the probability values in the above equation. The joint probability value signifies the blockchain adoption probability, with higher joint probability value, implying a high likelihood of adopting the blockchain technology in the organization.

5.4. Model evaluation and validation

GENIE 2.3 software was used to construct the Bayesian network analysis with observed prior probabilities. The simulation results with prior conditional probabilities (PCP) and revised conditional probabilities (RCP) for the two states (Low and High) of the independent variables namely; RA: Relative advantage, Top management support, Compatibility, Training & Education, Perceived financial benefits, Technical know-how, Competitive pressure, Partner readiness were calculated. For example, if an organization rates the conditional probability for Relative advantage (high state) as 0.2 from 0.375 in the developed Bayesian network model, we observe that there is no change in the posterior conditional probabilities of the dependent variables Perceived ease of use and blockchain adoption, with a negligible change in the conditional probability of Perceived usefulness (HIGH state) from 0.58 from 0.61. This signifies that the variable relative advantage is not a highly influential variable in the Bayesian network. To obtain more profound insights on the influence of the selected variables on the blockchain adoption in our Bayesian network, we estimated the influence of each variable on the dependent variable (blockchain adoption) using GENIE 2.3 software. The strength of the influence of all the variables is shown in Fig. 2.

The strength of influence values shown in Fig. 2 identifies Competitive pressure (0.420) as the most influential variable that has a significant effect on the blockchain adoption in the Indian supply chain followed by Perceived usefulness (0.358) and Perceived ease of use (0.215). The study reveals that Training & education, Perceived ease of use, and Relative advantage plays an essential role in developing the Perceived usefulness. It is further found that the perceived ease of use is an outcome of strong technical know-how on the use of blockchain, the complexity of the supply chain, perceived financial benefit, and training & education imparted to the employees.

The developed Bayesian model is based on theoretical structure, validated by using SEM. However, we performed necessary validation tests on the Bayesian network analysis using GENIE 2.3. The *Test only* method of validation was used to validate the developed model as the structural model was based on the theoretical concepts in technology adoption literature and not learned from the dataset. The Blockchain adoption variable was selected as the predictive variable, resulting in an overall accuracy of 88.33%. The highest accuracy of 94.4% was achieved for predicting the high state of blockchain adoption. The model predicted a low state of blockchain adoption with 36%. The Area Under Curve- Receiver Operator Characteristics (AUC-ROC) curve for the high state of blockchain adoption was plotted to examine the performance of the classification model using GENIE 2.3. The AUC-ROC curve shown in Fig. 3, shows a satisfactory performance of the developed model. The obtained ROC compares satisfactorily against the diagonal line representing a hypothetical baseline ROC. The same is represented numerically with the AUC value (0.6166).

It is learned from our Bayesian network analysis that when the probability threshold is $p = 0.5$, the network achieves a sensitivity of 0.45 and specificity of 1–0.3157=0.6843. The findings of our study reveal that the Bayesian network analysis performs better in predicting the high state of blockchain prediction in the supply chains as compared to the low state of blockchain prediction. Hence, we recommend that the validated Bayesian network model is used for predicting the high probability of adopting blockchain in the supply chains.

6. Discussion and implications

The study offers practitioners a refined Bayesian structural model validated using SEM for predicting the blockchain adoption in supply chains. The marginal log-likelihood value obtained for the prediction model with the probability of evidence (p(e)) set to high blockchain

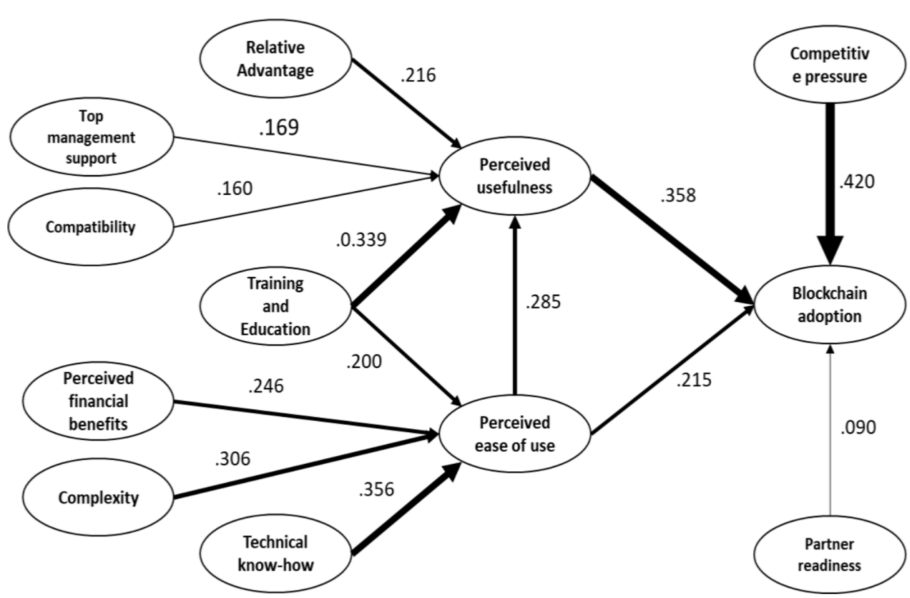

Fig. 2. Bayesian Network Influence Diagram.

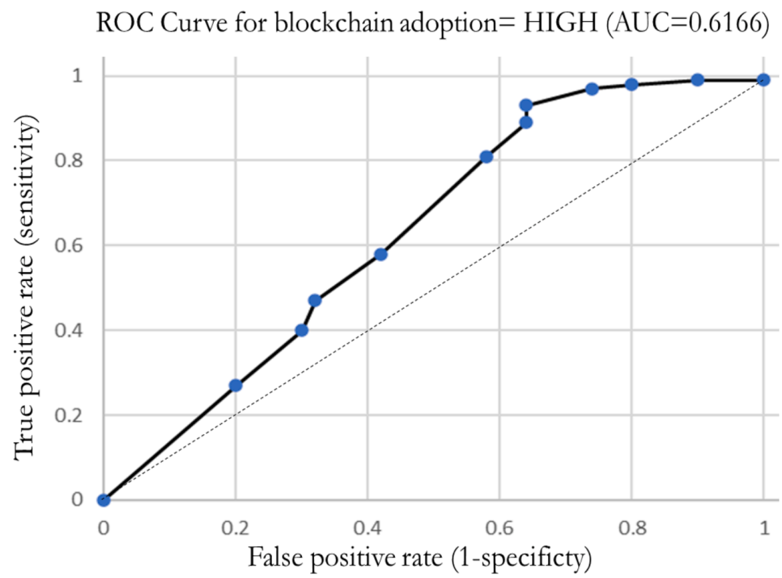

Fig. 3. AUC-ROC Curve.

adoption was -0.1244, which is highly satisfactory considering the number of variables used in the model. The use of the SEM model for validating the theoretical model in the context of blockchain adoption in an emerging economy such as India has helped in the identification of insignificant variables not contributing to the performance of the Bayesian network analysis. The findings of the present study imply that the use of SEM complements the Bayesian prediction model. It was found that the overall prediction accuracy of the Bayesian network analysis was 88.33%, and 94.4% for predicting the high state of blockchain adoption. The Bayesian network analysis identified perceived ease of use, perceived usefulness, and competitive pressure as the immediate parents (independent variables) influencing the blockchain adoption. Previous empirical studies by Kamble et al., (2019), Queiroz and Fosso Wamba (2019) support these findings. However, in this study, we have also identified the antecedents of perceived usefulness and perceived usefulness using the factors from the TOE framework, which has not been studied earlier in the literature.

The dynamic capability theory applied to the adoption of blockchain technology emphasizes the importance of developing the required resources and capacity. Adaptation to the changing environment is a dynamic capability that refines an organization's product innovation capability and reduces product risk (Pavlou and El Sawy, 2011). Adapting organizations have the advantage of being the first mover and, thus, remain competitive (Eisenhardt and Martin, 2000). There are a lot of discrepancies in information and product flows within a complex supply chain that affects customer satisfaction and overall efficiency. Organizations may not like to lose on this front in the ever-increasing competitive market and therefore perceive blockchain to be a strategic advantage over its competitors (Haoyan et al., 2017; Kamble et al., 2019). The importance of competitive pressure as an important influencer to blockchain technology adoption supports the dynamic capability theory emphasizing that organizations develop new capabilities in pursuit of improved competitive position (Carter and Koh, 2018).

The influence of perceived ease of use and perceived usefulness implies that organizations who perceive blockchain technology to offer increased utility as well as being easy to use, have a high probability of adopting blockchain. The probability of high perceived ease of use was found to be dependent on the technical know-how of the blockchain, the complexity of the supply chain, perceived financial benefit, and the regular training and educational programs imparted to employees at regular intervals. Technical know-how was found to be a critical factor in influencing the perceived ease of use, as India is yet to see successful blockchain adoptions within supply chains as compared to more developed economies (Queiroz and Fosso Wamba, 2019). Successful validations in Indian organizations will provide more exposure to implementation managers to improve their implementation skills. The complexity of supply chains is perceived to hurt the ease of use. The complexity of a supply chain refers to the efficiency that is required to be achieved for data integration, blockchain design, and functionality, integrating all supply chain partners. Blockchain-enabled global supply chains to operate in a complex environment that requires various parties to comply with various laws, regulations, and institutions.

Implementing a blockchain in such a situation is an incredibly complex task. It is, therefore, implied that practitioners would develop new blockchain applications that will help to integrate highly complex supply chains. Practitioners are required to explore the use of blockchain as a relationship-building technology focusing on resolving the complex and constraining effects of the blockchain (Hald et al., 2019). Min (2019) identified that complexities involved in the supply chain transactions lead to issues such as scalability, interoperability, and government regulations, leading to practitioners' perception of blockchain as a challenging technology to use. It is therefore implied that the organizations with relatively limited resources or experience in adopting such technologies should not underestimate the difficulties associated with the implementation of more sophisticated technology, despite the many best-practice cases found on technologically sophisticated early adopters (Angelis and da Silva, 2019). Training &education help employees in an organization to understand the technical and functional aspects of blockchain technology. A better understanding of the blockchain technology will make employees more knowledgeable and help them to overcome the fear and improve their perceptions on both ease of use and usefulness. It is therefore implied that for improvement in the probability of perceived ease of use, organizations should develop reliable and practical training modules. This will help them to develop a highly skilled and talented workforce facilitating the blockchain adoption process. Improved knowledge and expertise will also help organizations to address issues arising due to supply chain and blockchain complexities.

Training & education was also found to influence the perceived usefulness of the blockchain. The other influencing factors resulting in a high probability of perceived usefulness of blockchain included relative advantage offered by blockchain over other technologies, compatibility with the existing practices, processes, and technologies, top management support, and perceived ease of use. Blockchain, as compared to other technologies, offers a high relative advantage on the dimensions of trust (i.e., reliability and information security) (Collomb and Sok, 2016), product safety and authenticity of transactions (Toyoda et al., 2017; Mackey and Nayyar, 2017), support in achieving sustainable supply chain goals (Saberi et al., 2018), thus enabling supply chain re-engineering (Chang et al., 2019). It is, therefore, implied that organizations with sustainable supply chain goals that are built on trust and confidence in transactions have a high probability of implementing blockchain.

Our study finds that the higher the compatibility of the blockchain with the existing technological architecture, processes, and practices, the higher the probability of increased perceived usefulness. It is therefore implied that managers should simplify their business processes and develop technical architecture before they move forward in implementing blockchain technology. More efforts will be required in developing an infrastructure that facilitates the blockchain adoption (Queiroz and Fosso Wamba, 2019). Training & education was found to influence the perceived usefulness of blockchain technology. The blockchain is a significant supply chain transformation process that requires huge support from top management. When employees realize the seriousness of the top management in implementing blockchain, they are bound to develop a perception that it will improve their organizational performance (Kamble et al., 2019; Queiroz and Fosso Wamba, 2019; Angelis and da Silva, 2019).

The technical knowledge available with the organization and the training and education initiatives to manage blockchain operations are essential drivers of perceived usefulness leading to adoption. The finding supports that blockchain technology capabilities are continuously evolving and follow the three learning mechanisms identified from the literature– experience accumulation, knowledge articulation, and knowledge codification process (Zollo and Winter, 2002; Becker and Huselid, 2006). Employee development, including imparting professional knowledge and preparing them for future technologies, is an essential factor in developing and sustaining individual and organizational capabilities (Chien and Tsai, 2012; Huang and Intarakumnerd, 2019). Value cannot be generated by information technology alone and must be complemented by human resources (Coltman and Devinney, 2013; Schuler and Jackson, 1987). The technical readiness through active human resource development will help the organization to dynamically adapt the rules and routines of the new technology (Teece, 2007). The perceived financial benefits accrued from blockchain provides a sense of perceived ease of use influencing the blockchain adoption. Partner readiness is an important predictor of blockchain technology adoption and supports the dynamic capabilities theory, identifying supplier and customer alliances as opportunities to add value, reduce costs and financial risks (Napolitano, 1997; Liao et al., 2010; Sambasivan et al., 2013). The top management support, which is another important dimension of organizational capabilities, is found to influence the perceived usefulness of blockchain technology and find support in the literature (Liao et al., 2009).

7. Conclusions and future scope for research

The existing studies on the blockchain technology adoption in supply chains are focused on analyzing the cause and effect relationships using behavioral factors such as perceived ease of use and perceived usefulness from an individual's perspective. The literature has identified in the past that the institutional factors that include the technological, organizational, and environmental factors influence technology adoption. The present study conceptualized blockchain technology as a dynamic capability that every organization should possess to remain competitive and analyzed the blockchain adoption behavior of the organizations using the theoretical lens of TAM and TOE frameworks. The findings support the underlying theory of dynamic capability by identifying competitor pressure, partner readiness, perceived usefulness, and perceived ease of use as the most influencing factors for blockchain adoption.

The study extends the findings by developing a decision support system based on these significant factors. Based on the Bayesian network analysis, a machine learning algorithm, the decision support system can be used by the decision-makers for predicting the probability of blockchain adoption in their organization. The use of the Bayesian network analysis helps the decision-maker to have a realistic understanding of the relationships that are expressed in probabilities. The study reports the prior probability values used for developing the Bayesian network, which may be used as indicators by the practitioners to predict their blockchain adoption probability. The practitioner will be required to substitute these probability values (high or low), as applicable to their organization to estimate the adoption probability. The Bayesian estimation in the developed model is based on the strength of influence between the significant influencing variables and the blockchain adoption. The use of a decision support system will help the decision-makers to assess their present adoption probability and develop adoption strategies.

7.1. Future scope for research

Similar studies in different supply chain contexts will be required to be conducted before generalizing the above findings. Other machine learning techniques such as Support Vector Machine (SVM) and its extensions may be adopted in similar environments, which are found to minimize the noise in the data due to the presence of outliers in training set improving the classifier performance (Nie et al., 2017). The findings of the present study are based on the perceptions of the supply chain practitioners in Indian manufacturing companies from the automobile, chemical, and pharmaceutical sectors. In addition, the sample size of 181 practitioners may be a limitation as it is found that machine learning models perform better when the database is extensive. Revised joint probabilities may be substituted in the validated model for the independent events to refine the model further and improve the learning quality. Finally, studies may be conducted on developing self-learning models based on different machine learning algorithms instead of model development based on theories, then validating the models using SEM analysis and testing the consistency of the self-learned model with the existing theories in the literature. The findings of such studies will be exciting and highly practical from the decision-maker perspectives.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sachin S. Kamble, Angappa Gunasekaran, Vikas Kumar, Amine Belhadi, Cyril Foropon

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