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Integrated blockchain and internet of things in the food supply chain: Adoption barriers

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ABSTRACT

Blockchain (BLC) and the Internet of Things (IoT) are two emerging technologies that have become popular among practitioners for improving the transparency, adaptability, and safety of any industry. This is especially critical for food security, as COVID-19 highlighted the vulnerability of food supply chain (FSC). However, Indian organizations are experiencing problems in implementing the integrated form of BLC-IoT due to limited knowledge and insufficient research. The current study aims to propose a conceptual framework to reduce the impact of adoption barriers against BLC-IoT in FSC. Thirteen key barriers were identified after a thorough literature review and consultation with experts. The relationship among barriers was established using Interpretive structural modeling (ISM) and Decision-making trial and evaluation laboratory (DEMATEL) methods. The analysis shows that the lack of government regulation and workers' low competency significantly influence BLC-IoT adoption. The results also indicate the intricacy of decision-making by demonstrating that 9 of the 13 barriers were a part of the linkage cluster. The study outcome will help practitioners in developing and planning strategies for effective adoption of BLC-IoT in FSC.

1. Introduction

Food supply chain (FSC) practitioners are becoming more concerned about food quality and safety because of the rising population, increasing food demand, and higher consumer awareness (Yan et al., 2020). According to Rezaei and Liu (2017), about 30 percent of consumable food is lost at various stages of the FSC due to the unavailability of appropriate resources and the limited use of advanced technologies. The adoption and efficient management of technologies at all FSC stage will significantly reduce food waste and improve food safety (Raut et al., 2019a). In developed countries, practitioners and governing authorities have recognized the importance of technologies and started food safety regulation policies, implementing effective strategies, and adopting new practices (Gokarn and Kuthambalayan 2017). In the last few years, growing awareness and modern technologies in FSC have reduced food waste to 14% (FAO 2020). The technologies associated with Industry 4.0 (I4.0), such as the Internet of things (IoT), cyber-physical system (CPS), big data, artificial intelligence (AI), and Blockchain (BLC) are playing a major role in enhancing Supply Chain (SC) flexibility (Fragapane et al., 2020), improving visibility with real-time data sharing capabilities (Fatorachian and Kazemi, 2018) and integrating Supply chain management with other domains for better customer services (Ardito et al., 2019; Chand Bhatt et al., 2021). The importance of IoT in linking with FSC has been highlighted by Ali et al.

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(2019), as it can help to monitor, control, plan, and optimize supply chains in real time. Notably, IoT and BLC have been recognized as being important in the FSC sector as they contribute to improved visibility, transparency, and security (Dey and Shekhawat, 2021). A blockchain (BLC) is a decentralized and public ledger database of authenticated records of all executed and shared transactions that cannot be removed from the system (Corsby et al., 2016).

The use of IoT in FSC has enabled real-time monitoring, data capturing, and data transfer capabilities (Coronado-Mondragon et al., 2020), while BLC technology delivers better reliability, product/service security and traceability (Behnke and Janssen, 2020). Integrating IoT and BLC would simultaneously enable data security, trust, visibility, reliability, and real-time information sharing facilities in FSC (Lezoche et al., 2020a,b). BLC with IoT can be used in agriculture to track and trace the different footprints to ensure food quality and safety. As an example, the company Siemens has developed IoT-based systems with blockchain applications to provide restricted information access to shareholders for improved privacy and security (Siemens, 2019). Despite the multiple benefits of BLC and IoT, there is a dearth of evidence and standard protocols for ensuring their practical application (Tsang et al., 2021). In a recent study Chowdhury et al. (2020) emphasized the necessity for more robust FSC based on new technologies like as IoT, BLC, bigdata, AI, and others in a recent study, which would aid practitioners and government authorities in developing long-term business plans. Though these smart technologies have been hailed as revolutionary, Indian organizations are still hesitant to implement them due to limited contextual knowledge, a lack of practical research results, and a lack of awareness of the myriad issues associated with the integration of BLC and IoT in FSC.

Hence, to resolve the above adoption problem, this study seeks to address a significant research question (RQ): *What are the barriers to the implementation of BLC-IoT in FSC in the Indian context? Based on this RQ, following research objectives (ROs) have been formulated:*

RO1: To identify the critical barriers hampering the effective implementation of integrated BLC-IoT in FSC.

RO2: To identify the contextual relationships among the identified barriers.

RO3: To assess the cause-and-effect relations between the adoption barriers.

To address RO1, RO2, and RO3, an integrated Mutli-criteria Decision Making (MCDM) approach was proposed. Adoption barriers were identified through a comprehensive literature review and validated with expert discussion. The Interpretative Structural Modeling (ISM) was used to identify contextual relations between barriers under consideration. To find the intensity and cause-effect relation among barriers, the Decision-making trial and evaluation laboratory (DEMATEL) method was used in this study.

The rest of the paper is structured as follows. The conceptual background and the literature review are covered in Section 2. In Section 3, the research methodology adopted for the study is explained in detail. Section 4 presents the results and analysis. The discussion of the results is covered in Section 5. Finally, the conclusion, the implications and the limitations of the work are presented in Section 6.

2. Literature review

The fourth industrial revolution, or Industry 4.0, is causing significant transformations and is pushing supply chains (SC) to establish technology-enabled business strategies (da Silva et al., 2019). Increasing digitalization and technology transfer are improving the SC by building, implementing, and incorporating an integrated solution (Cho et al., 2022) for enhancing the flow of goods, information, and capital among stakeholders (Gong and Ribiere, 2021). With the increasing use of technologies in other sectors, the agriculture SCs have also started managing smart technologies to enhance food quality, food security, and data privacy to meet consumer expectations (Yadav et al., 2020a,b; Ozdemir et al., 2022). Among all of the smart technologies, BLC and IoT are promising technologies in SC, ensuring effectiveness, accuracy, and faster information sharing (Fan et al., 2020). Technology like IoT can be integrated with public and private blockchain, which have different regulatory aspects but similar quality in terms of SC management (Giri and Manohar, 2021). The utilization of private blockchain in the SC requires agreement and validation based on the needs and norms of the network. On the other hand, public blockchain in the SC is accessible for all, meaning that anybody can join the network (Cole et al., 2019). In India, a ban on crypto currency is hampering blockchain technology due to the transaction fees that must be paid. Also, even if a few organizations are providing the facilities of private block chains, the lack of availability of any legal and regulatory system is creating trust issues among SC players. In the present study, the term blockchain represents use of private blockchain only.

2.1. Blockchain adoption in supply chain

The BLC safeguards the information, verifies, and stores it through the application of various nodes. BLC is expanding in several fields because of its advantages and characteristics like transparency, decentralization, and cybersecurity (Gourisetti et al., 2020). Queiroz et al. (2019) highlighted the importance of BLC as a technology that can transform the SC by improving operations, data security, trust, and the relationship between different stakeholders. However, the technology acceptance model developed by the authors highlighted the behavioral challenges (performance expectancy, social influence, facilitating conditions, trust among stakeholders, and behavioral intention and expectation). Wang et al. (2019) listed trust, product and public safety, and SC complexities as critical drivers for blockchain deployment. Fan et al. (2020) stated that SC should adopt BLC when customers are more aware of tracking, tracing, and quality of products, and argued that manufacturers should be ready to cover higher costs to increase SC's benefit compared to retailers and suppliers. In contrast, retailers must share a specific percentage of the income with the manufacturer, who should pay a specific portion of profits with his suppliers. Hasan et al. (2020) discussed the 'transactional cost principle' for implementing BLC, and reported that the business with a higher capital structure would get more advantages in terms of stability and confidence. Some researchers such as Schuetz and Venkatesh (2020) addressed that blockchain could connect rural Indians to the global SC while improving financial situations. Similarly, Yadav et al. (2020) identified 'traceability,' 'real-time information availability to agro-stakeholders,' and 'decentralized and immutable database' as the significant drivers for blockchain adoption. Despite multiple advantages in the agriculture supply chain, the 'lack of government regulation' and 'lack of trust among stakeholders to use BLC' restrict the efficient adoption of BLC (Yadav et al., 2020). Orji et al. (2020) presented the Technology-Organization-Environment (TOE) framework for freight logistics, and identified the 'availability of specific BLC tools,' 'infrastructural facility,' and 'government policy and support' as the most critical barriers. Durach et al. (2020) explained that verified customer reviews and product quality certification were the most relevant blockchain features to be used for SC transactions while Kouhizadeh et al. (2021) identified technological challenges as the most critical barriers to BLC adoption. Musigmann et al. (2020) discussed how lack of essential resources, quality of data, real-life cases, and required infrastructure might cause the slow adoption of BLC and suggested involving IoT with BLC for future research. Although, Sharma et al. (2021) highlighted different barriers to adopting BLC technologies for the hospitality and tourism sector, it cannot be extrapolated to the food supply chain sector because hospitality and tourism belong to the service sector, while FSC is more towards the primary sector due to the direct involvement of farmers.

2.2. IoT adoption in supply chains

Over the last decade, the interest in Internet of Things (IoT) has grown exponentially as the technology allows real-time monitoring, data collection, and transmission (Delgosha et al., 2021). As stated by Atzori et al. (2010), IoT is a "worldwide network of interconnected objects uniquely addressable, based on standard communication protocols". IoT implementation can provide potential benefits if the organization considers critical success factors technical, operational, and resource challenges before being adopted in SC (Haddud et al., 2017). In terms of information exchange, data collection, and demand choice, the external (suppliers-manufacturer-retailer) and the internal integration (cross-operational) of IoT with SC would increase the operational capabilities and capacity (de Vass et al., 2018). However, organizations are more concerned with the cost of IoT technology, trust, and the perceived advantages (Tu 2018, Martens et al., 2021). The opportunity map of IoT adoption presented by Caro and Sadr (2019) described their benefits, such as supply-demand balance, accountability, stability, authorization, reduced ransomware risk, and improved cybersecurity in the SC network. Sestino et al. (2020) describe IoT as enablers of business digitalization strategy, allowing the SC organization to transform and optimize the conventional working process. According to behavioral reasoning theory, knowledge and training programs for implementing IoT in the agricultural sector would reduce the impact of perceived uncertainty, image barrier, price, and technical uneasiness (Pillai and Sivathanu 2020). Implementing IoT devices into SC will improve transparency, traceability, quality, and agility. It would enhance performance by facilitating information flow with vendors, further assisting demand forecasts, inventory planning, timely distribution, receipt, and quality assurance (de Vass et al., 2020).

2.3. Integration of blockchain and IoT

Both the BLC and the IoT are considered significant innovations individually. As a transparent, transactional database, BLC unlocks the capacity to generate and process information. Simultaneously, IoT describes the proliferation of embedded devices that can deliver data connectivity through a communication protocol. Integrating these two technologies might bring many advantages (Siegfried et al., 2018). However, the integration of BLC with IoT is challenging due to constraints like scalability, low internet bandwidth, storage capacity, data privacy due to IoT security problems at a different stage, legal permissions, and resource limitation (Reyna et al., 2018). Tsang et al. (2019) presented a BLC-IoT mechanism to help the Food Supply Chain (FSC) players get efficient and reliable tracking information and goods master data. Integration of BLC-IoT helps identify authentication, accountability, and data access control and reporting to address IoT privacy and security problems (Alsuwaidan 2020; Hong et al., 2019). The integration will facilitate scalability by reducing third parties' involvement in the business process (Viriyasitavat et al., 2019; Badulescu and Cheikhrouhou, 2021). The practitioners need to develop data validation strategies to authenticate the data collected from IoT devices before processing them into the BLC since inaccurate or invalid data can cause trust-related issues (Alsuwaidan, 2020).

2.4. Blockchain- Internet of Things (BLC-IoT) in the food supply chain

Food supply chain is a multiplayer distribution structure comprising producers, shipping companies, dealers, distributors, and consumers (Coppolino et al., 2020). The trade of agricultural products between these players is based on a bargaining mechanism with little value exchange (Kamilaris et al., 2019). Information on goods such as origin, process, quality, or environmental footprints can hardly be traced and tracked when they are purchased on the local market, resulting in food safety and security concerns. Kuokkanen et al. (2019) discussed the lack of transparency related to 'how and where food is produced and grown,'

Table 1
Barriers influencing adoption of Blockchain and Internt of Things: Review of literature.

Author(s)	Barriers	Description
Reyna et al. (2018); Chen et al. (2020); Singh et al. (2020); Sousa et al. (2020) Zahoor and Mir (2021)	Legal Permission	The organization needs legal permission from the government as crypto currencies used for BLC transactions are illegal in many countries. The absence of centralized authorities and regulations has increased the chances of using these technologies for fraudulent purposes. Existing laws or regulations, particularly after the advent of new disruptive technologies, are becoming outdated and need to be updated. In the Indian context, the lack of availability of any law related to the blockchain is acting as a major issue for the BLC-IoT implementation.
	Scalability and storage issues	BLC is not designed for extensive storage of data generated from IoT. Data transfer and data capacity are significant issues in the integration process. IoT devices can produce gigabytes of records in real-time, where as compared to IoT, BLC has fewer transactions per second. Compared to public BLC, private blockchain solutions have higher throughput.Still, BLC seems unsuitable for integration with IoT in this context.
	Resource constraints	IoT devices have a 'limited-resource nature' restricting their integration with the BLC consensus mechanism. A broad range of protocols for consensus exists, and the needs for resources (bandwidth, routing protocol, energy, and communication & computational capabilities) rely on the specific category of consensus mechanism. The limited resource existence of devices leaves them inadequate for BLC-IoT integration.
	Data reliability and security	The growing number of IoT data breaches makes it essential to develop more comprehensive cybersecurity. IoT sensors start operating correctly due to an environment or breakdown that glitches the system's data leaks. BLC can maintain data security and accept the modification, but the data remain unreliable if corrupted data are collected. Thus, corrupted data received from IoT devices may cause more problems if they are stored in BLC.
Astill et al. (2019); Feng et al. (2020); Lei et al.	High cost of technology	Technologies associated with BLC-IoT for FSC mainly

(continued on next page)

Table 1 (*continued*)

Author(s)	Barriers	Description
(2020); Lockl et al. (2020)		consist of biosensors, which are comparatively costly. It also includes continuous maintenance of the environment, power supply, and storage after implementation.
	Lack of public awareness	Public awareness and pessimistic thoughts are the major barriers to adoption. There is uncertainty about consumers' behavior about the rise in the cost of goods and accountability services.
	Lack of data ownership	Ownership of data grants access and control to data produced from IoT devices. It is unclear who is responsible for the final data produced from IoT devices, i.e., whether it belongs to the producer, shipping agency, or the participants who send/receive the food items. Due to the involvement of multiple stakeholders' data, responsibilities and ownership are major concerns.
	Lack of interoperability regulation	Interoperability amongst stakeholders and various data handling and processing systems in the FSC are essential. It can be defined as the capability of multiple stakeholders, individuals, or structures to function effectively. There are no unified FSC regulations for the organized use of emerging technology and their data. This may lead to limited or no access to information for some FSC actors.
	Low-speed communication	Internet is necessary for the continuous operation of BLC-IoT. Connectivity and installation of IoT devices with a central cloud system is a critical issue in rural areas having limited or no access to a high-speed communication.
Viriyasitavat et al. (2019); Wang et al. (2019); Lashkari and Musilek (2021)	Time for finality settlement of transactions	Finality guarantees the integrity of BLC-IoT network transactions. The delay in submitting a final settlement is challenging due to the size and the consensus protocol, particularly in time-critical operational activities associated with IoT devices.
	Lack of trust	Due to limited real examples of implementation, the integration of BLC-IoT is still not evident in terms of profitability and efficiency in FSC. Also, to maintain consistency in the performance of BLC-IoT the processes rely on the software interface. Thus, error probability always exists causing trust issues among practitioners.
	High resource consumption	The addition of the new BLC's consensus protocol is resource-consuming, which might not be acceptable for IoT devices with limited resources. These protocols require much time to create a block and immense computations for block mining, which is not suitable for IoT's fast flow information system. Although in SC, all of the participants know each other most of the time, and adding a player can require building new blocks that can be resource-consuming.
Makhdoom et al. (2019); Wang et al. (2019)	Lack of consensus protocol	The consensus protocol is the structure (set of rules) that allows the transaction to be agreed upon. The selection of IoT devices in BLC-IoT infrastructure depends upon the type of consensus protocol. Current general-purpose and consensus-oriented cryptocurrency protocols cannot maintain the highest possible faulty/untruthful nodes and are inappropriate for the integrated BLC-IoT framework. For example, no BLC consensus protocol is available for validating the device and its runtime.
	Lack of resources	Extra memory and computing costs are needed for integrating the IoT system with the BLC. Full and minor nodes must store the correct copy of the ledger, which is hardly possible with BLC's current storage capacity.
Rane and Narvel (2019); Alsuwaidan (2020); Sharma et al. (2022b); Sharma et al. (2022b); Zhao et al. (2020)	Lack of data regulation	No proper and standard data processing and data validity strategy is available to manage and process the data generated from IoT networks. Effective data regulation is needed for data privacy, control, and access.
	Low competency of workers	Untrained employees with a shared understanding of modern technologies are critical for FSC organizations. Developing expertise is a complex task because it requires a collection of factors (people, skills, abilities, and knowledge). To implement this new technology, users need to learn with BLC-IoT-enabled equipment and systems. Since most processes are controlled to meet the necessary safety layer, a self-aware workforce adds more value in adopting BLC-IoT devices.
	Low attitude towards adoption	The lack of availability of recognized benefits, user comfort, and no perceived reputation lower the adoption rate of new technologies.
Tran et al. (2020), Chirumalla (2021)	Lack of business process orchestrator	Business Process Orchestrators organize and

(*continued on next page*)

Table 1 (*continued*)

Author(s)	Barriers	Description
		document the functions and adoption process of IoT devices, equipment, and human operators to perform business interactions, like sharing renewable energy, leasing information, and providing software updates. No such structured process management and activities developed for BLC-IoT adoption share assets tracked, produced and consumed while utilizing the integrated system in FSC.

and 'no footprints for traceability, integrity, and food waste' as modern FSC problems. As various aspects of food waste involve organizational, operational, technical, and economic changes (Irani et al., 2018), organizations have started adopting and managing modern technologies that can enable food security and transparency in FSC. Kaur (2019) addressed the e-governance and policy initiatives as the biggest factors for driving IoT-based food security system for improving food safety in India. Astill et al. (2019) reported BLC and IoT-enabled technological systems as potential solutions for achieving transparency in FSC if the cost is not an issue for the organizations. Osmanoglu et al. (2020) explained that IoT devices used in FSC could be controlled and monitored remotely, and the security concern can be taken care of by integrating it with the distributed ledger that would provide secure transactions of information. Köhler and Pizzol (2020) discuss the tradeoff between advantages (accountability, trust, traceability, authenticity) and disadvantages (permission and participation of stakeholders, transaction time, scalability issues) of implementing BLC in FSC. Adopting a technology like BLC and IoT in FSC will drive the electronic culture, the concept of agriculture 4.0, and smart agriculture for improving food security and customer services (Chen et al., 2020; Lezoche et al., 2020).

From the practice point of view, Walmart has started tracking foods (meat and poultry, dairy products, multi-ingredient products, fruits, etc.) using an IoT-enabled blockchain technology called Hyperledger fabric (Hyperleadger, 2019). The World Wildlife Fund-Australia has begun developing OpenSC, which will allow the BLC-IoT to assist customers in preventing illicit and unsafe food products (WWF, 2019). Oracle is developing an integrated BLC-IoT platform to trace, track, and effectively pull recall products along the food supply chain (Hall and Ram, 2020). However, with limited disclosure of its practical advantages, the BLC-IoT integration and implementations remain theoretical (Ali et al., 2019) or under-developed needing innovation and future applications. Based on the literature survey above, adoption barriers of the integration BLC-IoT have been identified and are listed in Table 1.

2.5. Research gaps

Despite abundant literature about IoT and BLC adoption in the supply chain, most research works consider the specific use of technology, with a marked scarcity of literature related to technology integration (Daim et al., 2020; Yalcin and Daim, 2021). In various literature, the necessity for a study on the integration of technology for FSC to improve food security, safety, and performance has been mentioned. In a recent study, Kaur (2019) and Musigmann et al. (2020) said that improving SC productivity requires addressing the difficulties of IoT integration with BLC. Therefore, this study attempts to identify the problems of integrating BLC-IoT in FSC in the Indian setting in order to guide local practitioners and fill the research gap described above. Furthermore, a review of the literature suggests that the use of a Multi-Criteria Decision Making (MCDM) strategy or empirical approach to assess the impact of interrelationships among the obstacles is limited or non-existent since most studies focus on theoretical viewpoints. However, Chan and Daim (2018) used hierarchical decision models to examine the Chinese pharmaceutical sector concerning prospective technology areas, development strategies, and different innovation resources. These models have also been used in road mapping robotics technology (Daim et al., 2013), assessment of university collaborative research centers, technology transfer capabilities (Lavoie and Daim et al., 2020), and big data projects (Barham and Daim, 2020).

Table 2
Tools and techniques employed.

Reference	The focus of the Study	Tools and Techniques
Zhang et al. 2021	Identification of lean barriers	Interpretive Ranking Process (IRM)
Raut et al. (2019)	Identification of barriers of sustainable textile and apparel SC	Interpretive Structural Modeling (ISM)
Moktadir et al. (2018)	Development of interrelation among sustainable supply chain barriers	DEMATEL
Moktadir et al. (2020)	Study of critical success factors for waste reduction	Best–worst method (BWM)-DEMATEL
Yadav et al. (2020)	Blockchain adoption barriers in Indian agriculture SC	ISM- DEMATEL
Ali et al., 2019	Identification of lean six sigma barriers in SC	ISM
Kumar et al. (2021)	Identification of smart technology adoption barrier in warehouse	ISM-ANP
Kumar et al. (2021)	Identification of Industry 4.0 and circular economy barrier in agriculture SC	ISM-ANP
Kumar et al. (2021)	Mapping of adoption barrier in the public distribution system	ISM-ANP

3. Methodology

The present study uses an integrated ISM and DEMATEL methodology to identify the barriers against BLC-IoT, and to assess the interrelationship intensity between the barriers. DEMATEL, ISM, and Analytical Hierarchy Process (AHP) are the most popular techniques used by recent researchers (Farooque et al., 2020; Sharma et al., 2022). The literature has shown that authors have also used integrated methods to investigate emerging technologies such as AHP-ISM (Sharma et al., 2022; Sharma and Sehrawat, 2020a), AHP-ISM-DEMATEL (Sharma et al., 2021a), and AHP-DEMATEL (Sharma and Sehrawat, 2020b). The details of these techniques and the corresponding authors are listed in Table 2.

As shown in Fig. 1, the study has the following three major components:

Stage 1: Literature review and discussion with experts for validation of the barriers.
Stage 2: Development of the research framework using ISM, and
Stage 3: Identification of cause-and-effect group using DEMATEL technique. The detail of each component is explained in subsequent subsections.
Stage 1: Initially, a comprehensive literature review allowed to identify the relevant barriers. The barriers identified from the literature were discussed with twelve Indian supply chain practitioners having a minimum average experience of ten years. The selected practitioners consisted of four experts from the R&D department having theoretical as well as practical knowledge of blockchain development. Also, three experts were members of the policy-making committee of a private organization. The group of experts also comprised of three members from government organizations, one from the 'Department of Agriculture, Corporation & Farmer Welfare India', and one from the academia. To ensure validation of several experts for the ISM technique, the number of experts is in line

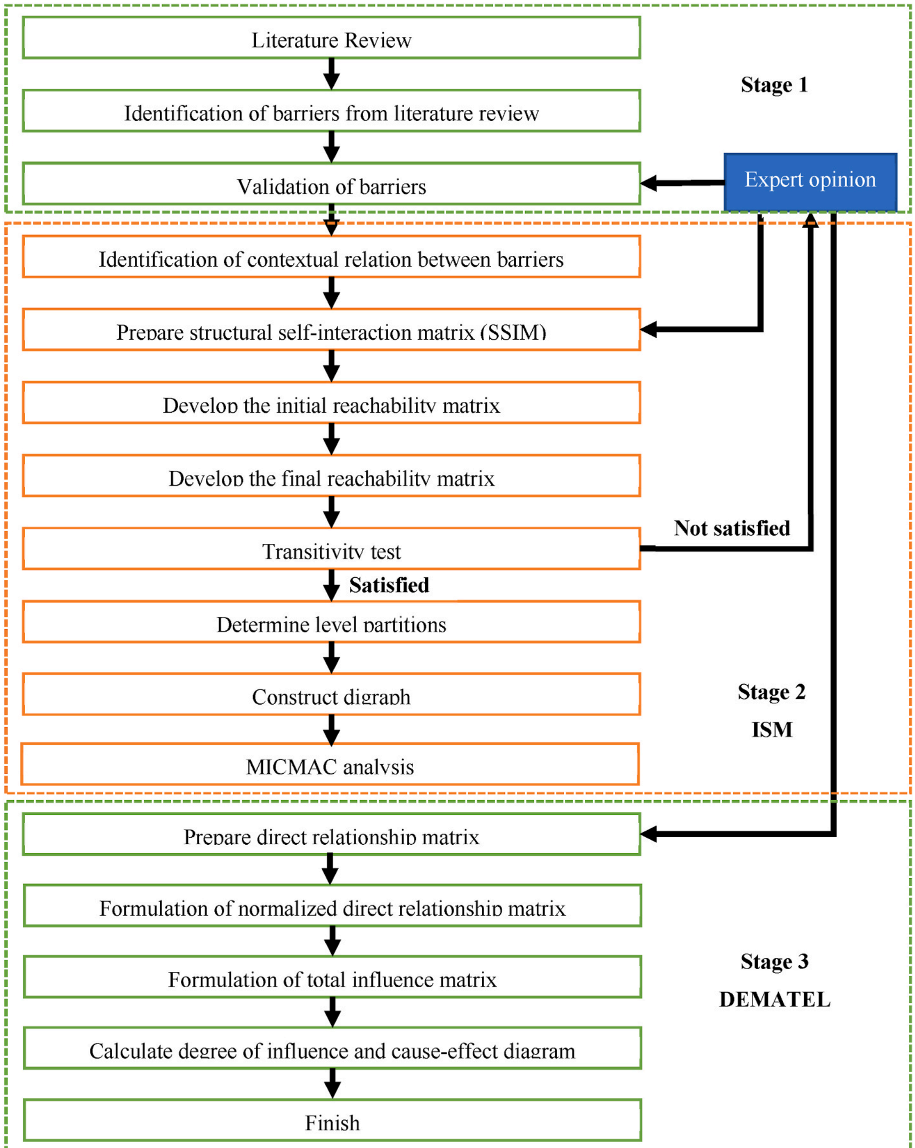

Fig. 1. Flow of research methodology.

with previous studies that stated that five to twenty expert opinions are required (Kumar et al., 2021a,b; Sharma et al., 2021). All the shortlisted barriers (Table 1) from the literature were discussed with experts. After multiple rounds of interviews/discussion with the experts, all the shortlisted barriers were classified as 13 critical barriers and 29 sub-barriers for further analysis, as shown in Table 3.

Stage 2 Interpretive structural modeling (ISM)

The ISM method is a well-known research tool among research communities to develop strategic frameworks, and to identify the relationship between factors, variables, enablers, and barriers (Kumar et al., 2021a,b). Interpretive structural modeling (ISM) was introduced by (Warfield 1974) for better decision-making when too many factors or constructs exist. It streamlines a complicated issue into a concise structure by forming a hierarchy (Yadav et al., 2020a,b). ISM has been commonly employed in many fields to model various complex problems because of its benefits over other MCDM approaches (Tavallaei and Ahmadi, 2018). ISM approach uses the finalized barriers of Stage 1 as input to identify the interrelationship among barriers and develop the adoption framework. The steps involved in the analysis of the ISM method are illustrated as below:

Step 2.1 The selected experts were requested to develop a “structural self-interaction matrix (SSIM)" that indicated a link between the proposed barriers (see Table 4) using L, M, N, and O where;
- L: if barrier i influences barrier j.
- M: if barrier i is influenced by barrier j.
- N: if both the barriers i and j are influencing each other.
- O: if there is no influence between the two barriers i and j.

Step 2.2 The SSIM was converted into an “Initial Reachability Matrix (IRM)" by substituting a binary number (0,1) for “L, M, N, O″ using a rule explained in Table 5.

Step 2.3 The IRM was tested for “transitivity” to get the “final reachability matrix (FRM)." In this step, some new interrelationships between barriers are established during the transitivity test. Transitivity was tested as, if barrier ‘i’ influences barrier ‘j’ and barrier ‘j’ influences barrier ‘k,’ then barrier ‘i’ indirectly influences barrier ‘k’.

Step 2.4 Level partition was performed to get the hierarchy of barriers to plot the directed graph or ISM model.

Step 2.5 ISM development is accompanied by an impact matrix cross-reference multiplication (MICMAC) analysis, where the

Table 3
Adoption barriers and sub-barriers of BLC-IoT for FSC.

Barriers	Sub- barriers	Reference of the evidence
Lack of resources (AT-1)	Storage issues; data transfer capabilities; need of extra memory; fewer miner nodes	Reyna et al. (2018); Makhdoom et al. (2019)
Lack of public awareness (AT-2)	No knowledge of modern technology; uncertain consumer behavior	Astill et al. (2019)
Lack of trust and privacy (AT-3)	Risk of exposure of private data; cyber issues	Chen et al. (2020); Viriyasitavat et al. (2019)
High investment cost (AT-4)	Cost related to technology; infrastructure development; training program; transformation cost	Sternberg et al. (2020); Astill et al. (2019)
Lack of government regulation (AT-5)	Legal permission; digital policies	Reyna et al. (2018);
High time for finality settlement (AT-6)	Stakeholders' coordination; low data handling capacity of BLC; low internet bandwidth	Chen et al. (2020); Viriyasitavat et al. (2019)
Lack of industry-standard (AT-7)	No structured process; less perceived benefit; no rules for asset sharing	Sternberg et al. (2020); Tran et al. (2020)
Lack of IT infrastructure (AT-8)	Unavailability of a digital platform; low internet speed	Astill et al. (2019)
Lack of data regulation (AT-9)	No ownership of data; no data validation strategy; data regulation issues	Alsuwaidan (2020); Astill et al. (2019)
Low attitude towards adoption (AT-10)	–	Alsuwaidan (2020)
Lack of consensus protocol (AT-11)	–	Makhdoom et al. (2019)
Low competency of workers (AT-12)	Unskilled; fear of change; fear of unemployment	Alsuwaidan (2020)
Lack of scalability and interoperability (AT-13)	Policies and information-carrying capacity	Reyna et al. (2018)

driving and dependence value of barriers were used as input to classify the barriers into four clusters:

(1) Autonomous: the barriers falling under this cluster have no connection with the system, and have low driving and dependence powers.
(2) Dependent: the barriers with weak driving power and high dependence power fall under this cluster.
(3) Linkage: the barriers within the linkage cluster are unstable, and are categorized by high driving and dependence powers.
(4) Independent or influent: the cluster's barriers are characterized by high driving power and low dependence. It is also considered as an influent cluster.

The ISM technique effectively presents the relationship between barriers, but it is inadequate for determining the intensity of that association. It also cannot provide the cause-and-effect relation among barriers that might confuse practitioners during the execution of the proposed framework (Yadav et al., 2020a,b). Hence, the DEMATEL technique is preferred over other research tools to overcome ISM's limitations for further analysis.

Stage 3 DEMATEL

The DEMATEL approach was used to evaluate direct and indirect cause-effect links among a collection of variables, and to identify the interaction's intensity (Asadi et al., 2021). The steps to carry out DEMATEL analysis are:

Step 3.1 The "direct relationship matrix" was established based on the opinion of experts. Experts' opinions were recorded for each barrier's influence on another by using an integer scale (0 for no influence, 1 for low influence, 2 for medium influence, 3 for high influence, and 4 for high influence). Given that k is the index of experts from a total of p experts, q is the index of the barriers, i and j are the indices for two barriers, the decision matrix of each expert is given by $[s_{ij}^{k}]_{q*q}$, then the "direct influence matrix" ($S = s_{ij_{q*q}}$)is given by Equation (1).

$$s_{ij} = \frac{1}{p}\sum_{k=1}^{p} s_{ij}^{k} i, j = 1, 2, 3.......q \quad (1)$$

Step 3.2 The "direct relationship matrix" was normalized using Equation (2).

$$D = \frac{S}{x} \quad (2)$$

where. $x = \left(max \sum_{j=1}^{q} s_{ij}, max \sum_{i=1}^{q} s_{ij}, \right); 1 \leq i \leq q$

Step 3.3 The "total influence matrix" was calculated by adding all the direct and indirect effects using Equation (3).

$$T = D + D^2 + ...D^h = D(I - D)^{-1} \quad (3)$$

Table 5
Conversion rule for IRM.

(i, j) in SSIM	(i, j) in IRM	(j, i) in IRM
L	1	0
M	0	1
N	1	1
O	0	0

Table 4
Structural self-interaction matrix (SSIM).

	AT-1	AT-2	AT-3	AT-4	AT-5	AT-6	AT-7	AT-8	AT-9	AT-10	AT-11	AT-12	AT-13
AT-1		O	M	L	N	O	L	O	L	M	M	M	L
AT-2			M	L	M	L	O	N	M	L	O	M	M
AT-3				O	L	O	N	O	N	O	M	L	O
AT-4					O	O	O	N	O	M	L	M	O
AT-5						O	M	O	L	M	O	L	M
AT-6							O	M	M	M	O	M	O
AT-7								O	N	O	M	O	N
AT-8									O	M	N	O	O
AT-9										O	M	N	O
AT-10											M	L	N
AT-11												O	O
AT-12													L

Table 6
Initial reachability matrix.

	AT-1	AT-2	AT-3	AT-4	AT-5	AT-6	AT-7	AT-8	AT-9	AT-10	AT-11	AT-12	AT-13
AT-1	1	0	0	1	1	0	1	0	1	0	0	0	1
AT-2	0	1	0	1	0	1	0	1	0	1	0	0	0
AT-3	1	1	1	0	1	0	1	0	1	0	0	1	0
AT-4	0	0	0	1	0	0	0	1	0	0	1	0	0
AT-5	1	1	0	0	1	0	0	0	1	0	0	1	0
AT-6	0	0	0	0	0	1	0	0	0	0	0	0	0
AT-7	0	0	1	0	1	0	1	0	1	0	0	0	1
AT-8	0	1	0	1	0	1	0	1	0	0	1	0	0
AT-9	0	1	1	0	0	1	1	0	1	0	0	1	0
AT-10	0	0	0	1	1	1	0	1	0	1	0	1	1
AT-11	1	0	1	0	0	0	1	1	1	1	1	0	0
AT-12	1	1	0	1	0	1	0	0	1	0	0	1	1
AT-13	0	1	0	0	1	0	1	0	0	1	0	0	1

Step 3.4 The "influence relationship map" was developed by adding elements of vector R (row) and vector C (column).

$$R = [r_i]_{q*1} = \left[\sum_{j=1}^{q} t_{ij}\right] \tag{4}$$

$$C = [c_j]_{1*q} = \left[\sum_{i=1}^{q} t_{ij}\right] \tag{5}$$

where r_i and c_j are the summation of ith row and jth column of the "total influence matrix", respectively.

These two vectors were used for creating an influence map by considering (R + C) as the x-axis called the prominence and (R–C) as the y-axis known as the relation for each barrier. If (r_i-c_j) is positive, then the barrier i is the one who influences other barriers, and if (r_i-c_j) is negative, then other barriers influence the barrier i.

4. Results and analysis

4.1. Proposed list of barriers

After an interaction with experts, the proposed barriers and their sub-barriers were finalized (Table 3). All of the sub-barriers can be used to understand the definition of their associated barrier. For example, Barrier AT-1 indicates storage issues, data transfer capabilities, shortage/need of extra storage space, and fewer nodes in the blockchain.

4.2. Result of ISM

4.2.1. Establish SSIM

As discussed in Step 1, the relationships between different barriers called SSIM are presented in Table 4. This matrix was developed based on the direct input of experts, and it represents the bi-directional relationship between two barriers at a time. For example, in the SSIM matrix, the association of (AT-1, AT-2) is represented by an "O," indicating that there is no link between these two barriers or that they do not influence each other. Similarly, M (AT-1, AT-3) indicates that AT-1 is influenced by AT-3, L (AT-1, AT-4) indicates that AT-1 influence the AT-4, and N (AT-1, AT-5) indicates that both AT-1 and AT-5 are influencing each other.

4.2.2. Formation of IRM

Transformation of SSIM matrix into IRM uses the binary rule shown in Table 4. For example, the entry of (AT-1, AT-2) in the SSIM matrix is "O," which is replaced by "0″ for (AT-1, AT-2) and "0″ for (AT-2, AT-1) in the IRM matrix (see Table 6).

4.2.3. Formation of FRM

FRM is formed after checking IRM for transitivity. This was done to represent all of the indirect connections to maintain the consistency of relationships among the barriers. For example, there is a direct relation between AT-3 & AT-1 and AT-1 & AT4, but there is no relation between AT-3 & AT-4 as shown in the SSIM matrix or Table 4. Hence, according to the rule of transitivity, there is an indirect relation between AT-3 & AT-4, corrected during the formation of FRM. It can be observed in Table 7, where the relation of AT-3 & AT-4 is represented by 1*. All of the asterisk signs represent the indirect relation rectified during the formation of the FRM matrix.

From the FRM matrix, the driving power (DP) and dependence

Table 7
Final reachability matrix.

	AT-1	AT-2	AT-3	AT-4	AT-5	AT-6	AT-7	AT-8	AT-9	AT-10	AT-11	AT-12	AT-13	DP
AT-1	1	1*	1*	1	1	1*	1	1*	1	1*	1*	1*	1	13
AT-2	0	1	0	1	1*	1	0	1	0	1	1*	1*	1*	9
AT-3	1	1	1*	1*	1	1*	1	1*	1	1*	0	1	1*	12
AT-4	1*	1*	1*	1	0	1*	1*	1	1*	1*	1	0	0	10
AT-5	1	1	1*	1*	1	1*	1*	1*	1	1*	0	1	1*	12
AT-6	0	0	0	0	0	1	0	0	0	0	0	0	0	1
AT-7	1*	1*	1	0	1	1*	1	0	1	1*	0	1*	1	10
AT-8	1*	1	1*	1	0	1	1*	1	1*	1*	1	0	0	10
AT-9	1*	1	1	1*	1*	1	1	1*	1	1*	0	1	1*	12
AT-10	1*	1*	0	1	1	1	1*	1	1*	1	1*	1	1	12
AT-11	1	1*	1	1*	1*	1*	1	1	1	1	1*	1*	1*	13
AT-12	1	1	1*	1	1*	1	1*	1*	1	1*	1*	1*	1	13
AT-13	1*	1	1*	1*	1	1*	1	1*	1*	1	0	1*	1*	12
DEP	11	12	10	11	10	13	11	11	11	12	7	10	10	

DP-driving power, DEP-dependence power.

Table 8
Level partition.

Barriers	Reachability set	Antecedent set	Intersection set	Level
AT-1	AT-1 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-11 AT-12 AT-13	AT-1 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-11 AT-12 AT-13	AT-1 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-11 AT-12 AT-13	3
AT-2	AT-2 AT-4 AT-5 AT-8 AT-10 AT-11 AT-12 AT-13	AT-1 AT-2 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-10 AT-11 AT-12 AT-13	AT-2 AT-4 AT-5 AT-8 AT-10 AT-11 AT-12 AT-13	2
AT-3	AT-1 AT-3 AT-4 AT-5 AT-7 AT-9 AT-12 AT-13	AT-1 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-11 AT-12 AT-13	AT-1 AT-3 AT-4 AT-5 AT-7 AT-9 AT-12 AT-13	3
AT-4	AT-4 AT-8 AT-11	AT-4 AT-5 AT-8 AT-11 AT-12	AT-4 AT-8 AT-11	4
AT-5	AT-5	AT-5	AT-5	6
AT-6	AT-6	AT-1 AT-2 AT-3 AT-4 AT-5 AT-6 AT-7 AT-8 AT-9 AT-10 AT-11 AT-12 AT-13	AT-6	1
AT-7	AT-1 AT-3 AT-5 AT-7 AT-9 AT-12 AT-13	AT-1 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-11 AT-12 AT-13	AT-1 AT-3 AT-5 AT-7 AT-9 AT-12 AT-13	3
AT-8	AT-4 AT-8 AT-11	AT-4 AT-8 AT-11 AT-12	AT-4 AT-8 AT-11	4
AT-9	AT-1 AT-3 AT-4 AT-5 AT-7 AT-9 AT-12 AT-13	AT-1 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-11 AT-12 AT-13	AT-1 AT-3 AT-4 AT-5 AT-7 AT-9 AT-12 AT-13	3
AT-10	AT-1 AT-2 AT-4 AT-5 AT-7 AT-8 AT-9 AT-10 AT-11 AT-12 AT-13	AT-1 AT-2 AT-3 AT-4 AT-5 AT-7 AT-8 AT-9 AT-10 AT-11 AT-12 AT-13	AT-1 AT-2 AT-4 AT-5 AT-7 AT-8 AT-9 AT-10 AT-11 AT-12 AT-13	2
AT-11	AT-4 AT-8 AT-11	AT-4 AT-8 AT-11 AT-12	AT-4 AT-8 AT-11	4
AT-12	AT-12	AT-5 AT-12	AT-12	5
AT-13	AT-1 AT-3 AT-5 AT-7 AT-9 AT-12 AT-13	AT-1 AT-3 AT-5 AT-7 AT-9 AT-11 AT-12 AT-13	AT-1 AT-3 AT-5 AT-7 AT-9 AT-12 AT-13	3

power (DEP) for each barrier are calculated. The DP is the summation of the value of all the row elements, while DEP is the summation of all the column elements corresponding to the respective barrier.

4.2.4. Level partition

Using FRM, a 'reachability set,' an 'antecedent set,' and an 'intersection set' for each barrier was developed. The 'reachability set' consists of barriers with a corresponding value of 1 in that row, and similarly, the 'antecedent set' consists of barriers with a corresponding value of 1 in that specific column. For example, for the Barrier AT-1, the reachability set includes 13 barriers represented by the value of 1 in the corresponding cell.

The 'intersection set' is the set of common barriers between the 'reachability set' and the 'antecedent set.' The obtained 'reachability set,' 'antecedent set,' and 'intersection set' are used for level partition. The barriers for which the 'reachability set' and 'intersection set' are the same as the ISM model's top level. After identifying the top-level barriers, they are eliminated from the list, and the same process is performed for the remaining barriers to obtain the hierarchy. The results of the different sets and the level iterations are shown in Table 8.

4.2.5. Formation of ISM model

ISM model is formulated based on the partition level of barriers. In the first iteration, the high time for finality settlement (AT-6) satisfied the necessary condition, which became part of Level-1. and was placed at the top of the ISM model. The second iteration resulted in second-level barriers involving lack of public awareness (AT-2) and low attitude towards adoption (AT-10), was placed below the first level. Similarly, in the third iteration, lack of resources (AT-1), lack of trust and privacy (AT-3), lack of industry-standard (AT-7), lack of data regulation (AT-9), and lack of scalability and interoperability (AT-13) formed the third level barrier, and was placed below the second level. Likewise, the fourth level barriers were obtained in the fourth iteration, which involved high investment cost (AT-4), lack of IT infrastructure (AT-8), and lack of consensus protocol (AT-11), and was positioned below the third level. Correspondingly, fifth (lack of competency: AT-12) and sixth level (lack of government regulation: AT-5) barriers were identified in the fifth and the sixth iterations. The developed framework or ISM model of barrier adoption is shown in Fig. 2.

4.2.6. MICMAC analysis

The MICMAC analysis is performed to identify barriers' behavior and the impact of barriers on the successful execution of the integrated BLC-IoT FSC system. The analysis showed that all of the selected barriers for this study were relevant as no barrier fell under the 'Autonomous' cluster (see Fig. 3). The barrier AT-6 'high time for finality settlement' was placed at the top of the model and fell under the 'Dependence' cluster. The barriers under the linkage cluster were volatile due to high driving and dependence power. Lack of resources (AT-1), lack of public awareness (AT-2), lack of trust and privacy (AT-3), high investment cost (AT-4), lack of industry-standard (AT-7), lack of IT infrastructure (AT-8), lack of data regulation (AT-9), low attitude towards adoption (AT-10), and lack of scalability and interoperability (AT-13) were categorized under the linkage cluster. Any decision related to linkage barriers needs continuous assessment and improvement to efficiently adopt integrated BLC-IoT in FSC. The Independent cluster is generally composed of the barriers at the bottom level ISM model. In the analysis, lack of government support (AT-5), lack of consensus protocol (AT-11), and low competency of workers (AT-12) were placed in the independent cluster. As these barriers are considered drivers for other barriers in the system, the organizations should prioritize them during the decision-making process.

4.3. Results of DEMATEL

The same pool of experts was invited to participate in the discussion and data collection for DEMATEL analysis. Practitioners assessed the barriers on a scale of 0–4 depending on the influence of one barrier over other barriers to obtain the direct relation matrix, as shown in Table 9. First, the direct relation matrix was converted into a normalized direct relation matrix (Table 10) using Equation (2). Furthermore, the normalized matrix was converted into a "total influence matrix" (Table 11) using Equation (3). Finally, the degree of influence was calculated using Equation (4) and Equation (5), as mentioned in the Step 3.4. The cause-effect matrix is shown in Table 12.

The outcome of DEMATEL analysis showed that six barriers: lack of resources (AT-1), lack of public awareness (AT-2), high investment cost (AT-4), lack of government regulation (AT-5), low competency of workers (AT-12), and lack of scalability and interoperability (AT-13) formed part of the cause group, which was driving the other seven barriers belonging to the effect group. Lack of trust and privacy (AT-3), high time for finality settlement (AT-6), lack of industry standards (AT-7), lack of IT infrastructure (AT-8), lack of data regulation (AT-9), low attitude towards adoption (AT-10), and lack of consensus protocol (AT-11) formed part of the effect group. The cause group barriers are always independent, while the effect group barriers are dependent. R + C value represents the centrality of the barrier on the adoption system, while the R–C value represents the impact on the other barriers.

4.4. Sensitivity analysis

The developed ISM-DEMATEL approach is subjected to sensitivity

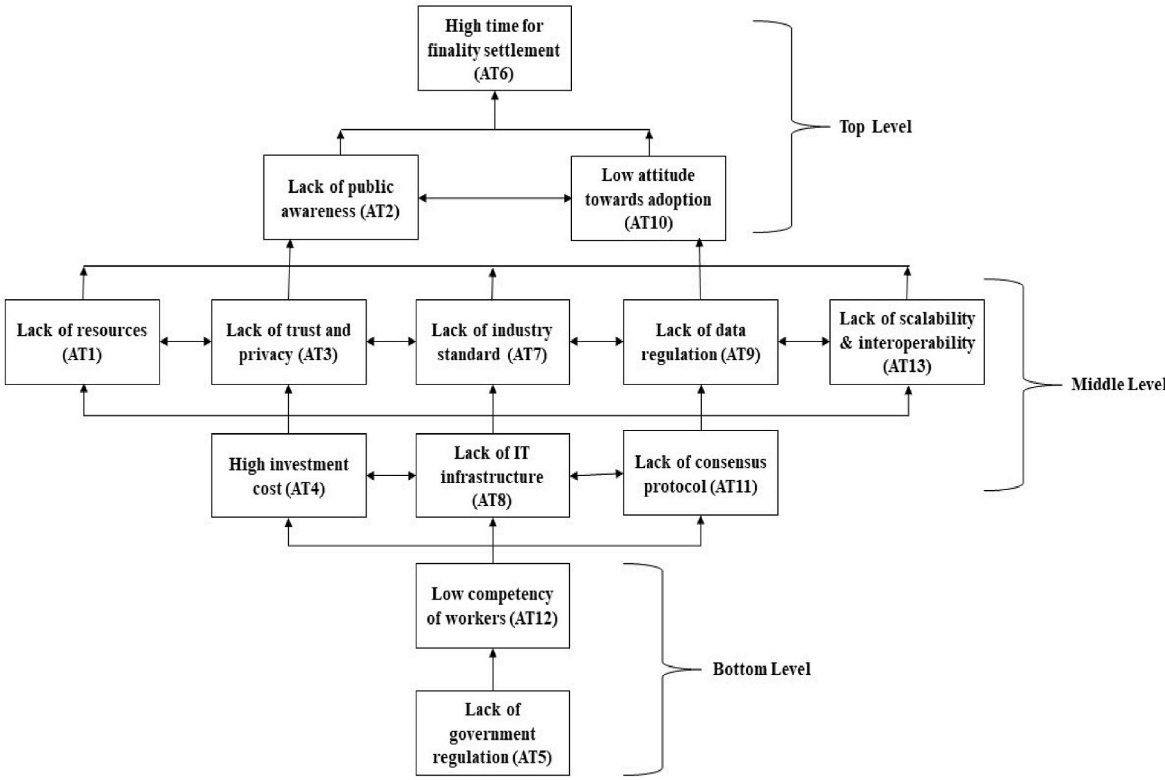

Fig. 2. ISM model.

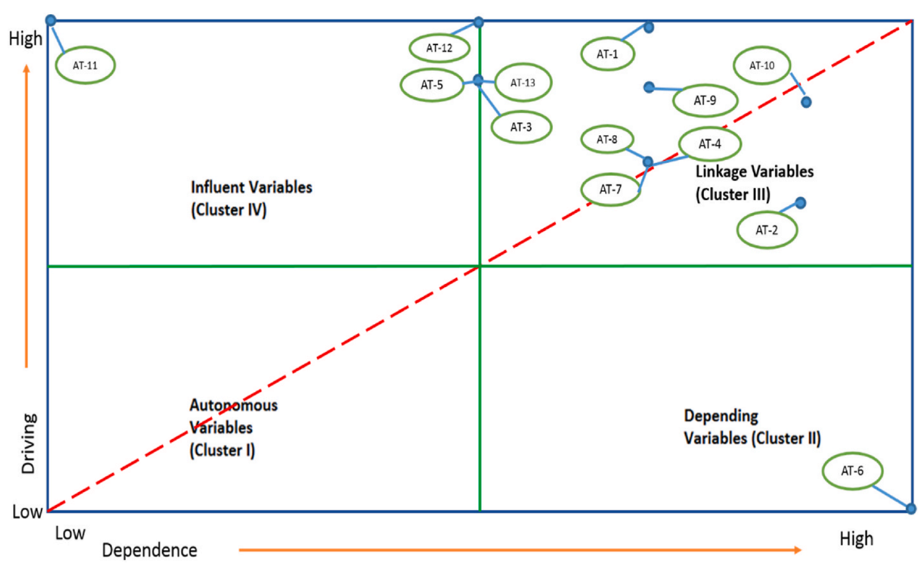

Fig. 3. Driver and dependence diagram.

analysis to verify the consistency of the calculated value, and to validate the stability of professional judgment. Sensitivity analysis is the method for determining the reliability of results. Each professional's input was given a distinct weighting, whereas the other professionals' input was equal (Moktadir et al., 2018). Four different total relationship matrices and other comparable matrixes were created for sensitivity analysis by multiplying each weight assigned to the different experts. The average relationship matrices were then constructed, and the cause-effect linkages between the various barriers were developed. Table 13 shows that the ranking of all barriers during four iteration of sensitivity analysis is the same as the base rank, which is also supported by a similar digraph obtained after sensitivity analysis, as shown in Fig. 4.

5. Discussion

The analysis shows that **"lack of government regulation"** is a major barrier against adopting BLC-IoT in the food supply chain, which is in line with results from recent studies (Daim et al., 2020; Zhang et al., 2021; Yalcin and Daim, 2021). This barrier received the highest R + C value (31.1854) and the highest R–C value (32.0370). This implies that a lack of government regulation has the highest impact on the adoption process and the other barriers. The presence of this barrier at the

Table 9
Direct relation matrix.

	AT-1	AT-2	AT-3	AT-4	AT-5	AT-6	AT-7	AT-8	AT-9	AT-10	AT-11	AT-12	AT-13
AT-1	0	4	4	4	4	2	3	3	1	4	3	4	3
AT-2	3	0	2	3	1	3	3	3	4	2	4	3	2
AT-3	4	2	0	4	4	4	4	4	3	4	3	4	4
AT-4	2	4	2	0	4	4	4	2	2	4	2	4	4
AT-5	3	1	4	3	0	2	4	4	3	1	4	3	2
AT-6	4	3	4	4	4	0	3	2	2	3	4	4	3
AT-7	2	4	3	4	4	3	0	3	2	3	3	4	4
AT-8	2	4	4	2	4	4	3	0	2	3	4	4	3
AT-9	4	4	3	3	4	4	4	2	1	2	3	4	2
AT-10	4	3	3	2	4	4	3	4	3	0	2	3	3
AT-11	4	4	4	3	4	4	4	4	4	2	0	4	4
AT-12	4	4	3	4	4	4	2	3	2	4	2	0	2
AT-13	4	2	4	4	4	4	4	4	4	4	4	3	0

Table 10
Normalized direct relation matrix.

	AT-1	AT-2	AT-3	AT-4	AT-5	AT-6	AT-7	AT-8	AT-9	AT-10	AT-11	AT-12	AT-13
AT-1	0.00	0.09	0.09	0.09	0.09	0.04	0.07	0.07	0.02	0.09	0.07	0.09	0.07
AT-2	0.07	0.00	0.04	0.07	0.02	0.07	0.07	0.07	0.09	0.04	0.09	0.07	0.04
AT-3	0.09	0.04	0.00	0.09	0.09	0.09	0.09	0.09	0.07	0.09	0.07	0.09	0.09
AT-4	0.04	0.09	0.04	0.00	0.09	0.09	0.09	0.04	0.04	0.09	0.04	0.09	0.09
AT-5	0.07	0.02	0.09	0.07	0.00	0.04	0.09	0.09	0.07	0.02	0.09	0.07	0.04
AT-6	0.09	0.07	0.09	0.09	0.09	0.00	0.07	0.04	0.04	0.07	0.09	0.09	0.07
AT-7	0.04	0.09	0.07	0.09	0.09	0.07	0.00	0.07	0.04	0.07	0.07	0.09	0.09
AT-8	0.04	0.09	0.09	0.04	0.09	0.09	0.07	0.00	0.04	0.07	0.09	0.09	0.07
AT-9	0.09	0.09	0.07	0.07	0.09	0.09	0.09	0.04	0.02	0.04	0.07	0.09	0.04
AT-10	0.09	0.07	0.07	0.04	0.09	0.09	0.07	0.09	0.07	0.00	0.04	0.07	0.07
AT-11	0.09	0.09	0.09	0.07	0.09	0.09	0.09	0.09	0.09	0.04	0.00	0.09	0.09
AT-12	0.09	0.09	0.07	0.09	0.09	0.09	0.04	0.07	0.04	0.09	0.04	0.00	0.04
AT-13	0.09	0.04	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.07	0.00

Table 11
Total influence matrix.

	AT-1	AT-2	AT-3	AT-4	AT-5	AT-6	AT-7	AT-8	AT-9	AT-10	AT-11	AT-12	AT-13	R- Sum
AT-1	−1.0	−0.1	8.1	−1.4	−6.3	0.2	0.0	0.9	0.0	0.7	5.2	−4.6	−1.3	0.39
AT-2	0.4	0.1	−13.7	2.3	10.9	−0.2	−0.1	−1.6	0.0	−1.2	−7.9	8.5	2.1	−0.45
AT-3	0.3	0.0	−13.4	1.8	11.0	−0.2	−0.1	−1.1	−0.5	−1.2	−7.2	8.0	2.3	−0.43
AT-4	−0.4	0.0	4.3	−1.3	−3.2	0.1	0.1	1.1	−0.2	0.4	2.6	−2.4	−0.6	0.27
AT-5	0.3	0.0	−12.4	1.8	10.0	−0.2	−0.1	−1.1	−0.5	−1.2	−7.2	8.0	2.3	−0.43
AT-6	0.4	0.1	−13.7	2.4	11.3	−0.3	−0.1	−1.6	−0.8	−1.3	−7.6	8.3	2.4	−0.54
AT-7	0.5	0.1	−0.4	0.6	0.2	−0.1	0.0	−0.6	0.2	−0.1	−0.7	0.2	−0.1	0.04
AT-8	−0.4	0.0	4.3	−0.3	−3.2	0.1	0.1	0.1	−0.2	0.4	2.6	−2.4	−0.6	0.27
AT-9	0.3	0.0	−12.4	1.8	11.0	−0.2	−0.1	−1.1	−1.5	−1.2	−7.2	8.0	2.3	−0.43
AT-10	0.2	−0.1	10.7	−2.0	−8.1	0.2	0.0	1.4	−0.2	1.0	5.4	−6.2	−1.8	0.46
AT-11	0.0	−0.1	8.1	−1.4	−6.3	0.2	0.0	0.9	0.0	0.7	4.2	−4.6	−1.3	0.39
AT-12	0.0	−0.1	8.1	−1.4	−6.3	0.2	0.0	0.9	0.0	0.7	5.2	−5.6	−1.3	0.39
AT-13	0.3	0.0	−12.4	1.8	11.0	−0.2	−0.1	−1.1	−0.5	−1.2	−7.2	8.0	1.3	−0.43
D-Sum	0.59	0.07	34.96	4.64	31.61	0.58	0.44	2.68	4.21	−3.39	19.78	22.91	5.74	

foundation of the ISM model solidifies the finding of DEMATEL. This finding aligns also with that of Köhler and Pizzol (2020), who highlight that government authorities' uniform rules and regulations and involvement in the technology implementation process would drive BLC-IoT adoption. Both governments and practitioners need to reduce its impact on other barriers to ease the adoption of BLC-IoT in the food supply chain. The government needs to collaborate and share the documented rules with the relevant organizations to effectively enforce regulations (Sharma et al., 2021). It is a government's responsibility to develop policies and set up legislation for promoting the use of technologies in the agriculture sector.

The "**low competency of workers"** is directly influenced by government regulations. It is the second most crucial barrier with an R–C value of 22.5149 and an R + C value of 23.3006. The high R + C value indicates its impact on the adoption process, while the high R–C value specifies its driving force over the other barriers. Both indicators categorize 'low competency of workers' as independent barriers, and hence solidify the study's outcome. This finding is in line with the outcome of Kumar et al. (2021), who stated that governments and organizations need to concentrate on workers' training and skill development to build a professional and motivated workforce in the food industry. In general, farmers get less access to information than other stakeholders in the FSC due to a lack of skills, remoteness of rural regions, and sedentary lifestyle. Therefore, the government should empower the farmers with open data and mobile services to overcome this skill imbalance. Mishra et al. (2018) also raise this issue, and state that adequate skills among SC organization workers are needed to transform the traditional working process.

The "**high investment cost"** is one of the significant challenges for FSC organizations. This barrier is a part of the linkage cluster, and the cause group with total impact value on adoption process (R + C) of 4.9043 and influence on other barriers (R–C) of 4.3723. Any decision

Table 12
Degree of influence.

	R	C	R + C	R–C	Coordinates in Fig. 4	
AT-1	0.59	0.39	0.9827	0.1969	Q (0.98, 0.19)	Cause
AT-2	0.07	−0.45	−0.3796	0.5286	Q (−0.37, 0.52)	Cause
AT-3	−34.96	−0.43	−35.3868	−34.5353	Q (−35.38, −34.53)	Effect
AT-4	4.64	0.27	4.9043	4.3723	Q (4.9, 4.3)	Cause
AT-5	31.61	−0.43	31.1854	32.0370	Q (31.18, 32.03)	Cause
AT-6	−0.58	−0.54	−1.1172	−0.0384	Q (−1.11, −0.03)	Effect
AT-7	−0.44	0.04	−0.3946	−0.4780	Q (−0.39, −0.47)	Effect
AT-8	−2.68	0.27	−2.4181	−2.9501	Q (−2.4, −2.9)	Effect
AT-9	−4.21	−0.43	−4.6400	−3.7884	Q (−4.64, −3.7)	Effect
AT-10	−3.39	0.46	−2.9288	−3.8550	Q (−2.92, −3.8)	Effect
AT-11	−19.78	0.39	−19.3880	−20.1738	Q (−19.38, −20.17)	Effect
AT-12	22.91	0.39	23.3006	22.5149	Q (23.30, 22.51)	Cause
AT-13	5.74	−0.43	5.3177	6.1692	Q (5.3, 6.16)	Cause

Table 13
Ranking obtained after sensitivity analysis.

	Rank obtained from R–C				
	base rank	iteration 1	iteration 2	iteration 3	iteration 4
AT-1	6	5	5	5	5
AT-2	5	6	6	6	6
AT-3	13	13	13	13	13
AT-4	4	4	4	4	4
AT-5	1	1	1	1	1
AT-6	7	7	7	7	7
AT-7	8	8	8	8	8
AT-8	9	9	9	9	9
AT-9	10	10	10	10	10
AT-10	11	11	11	11	11
AT-11	12	12	12	12	12
AT-12	2	2	2	2	2
AT-13	3	3	3	3	3

related to this barrier can drive the results of other barriers as the operations related to the development and administration of BLC and IoT technologies are costly compared to traditional operational processes (Choi 2020). It involves all the direct and indirect costs of infrastructure development, training, and hardware and software purchase. This outcome is akin to the findings of Rahman et al. (2021), who considered the high cost of switching from one technology to another. Although the implementation is costly, Musigmann et al. (2020) demonstrated that leveraging BLC-based smart contracts to automate operational procedures might create incentives for SC practitioners by reducing administration and personnel costs.

The implementation process needs huge infrastructure change, as there is a "**lack of IT infrastructure"** for Internet services and IoT devices. Lack of IT infrastructure is part of the effect group driven by barriers such as government regulations and financial support. This finding is in line with the outcome of Yadav et al. (2020a,b). Recognizing the quantity and percentile of food wasted at every stage of the FSC regarding monetary losses may encourage stakeholders to invest in technologies. As "**lack of consensus protocol"** is a significant barrier in developing the BLC-IoT integrated system, the organization's high investment would help build infrastructure and more consensus protocols

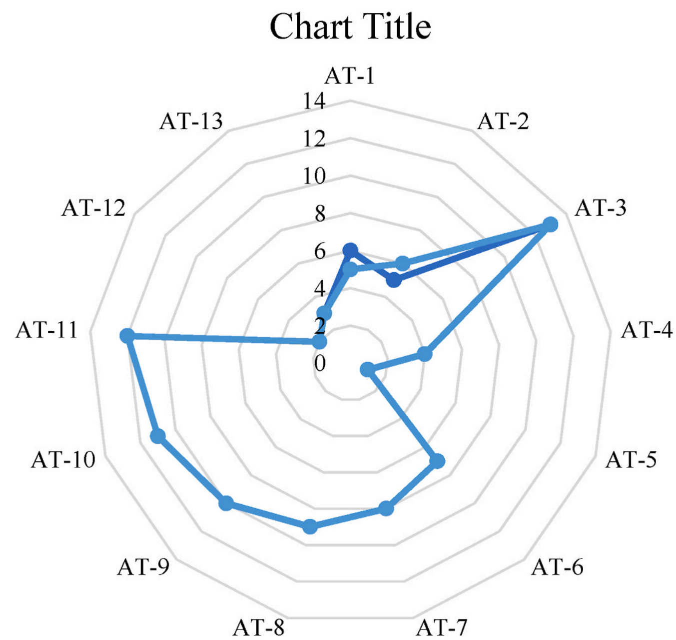

Fig. 4. Digraph obtained during sensitivity analysis.

to improve the adoption process. Makhdoom et al. (2019) also underscored the importance of consensus protocol, and explained that a sufficient number of protocols is needed for secure transactions in the BLC-IoT network. The throughput accuracy and speed depend upon the number of users accessing the node, which directly depends on the number of separate consensus protocols in the BLC-IoT system (Wang et al., 2019b).

The "**lack of scalability and interoperability"** is the third most substantial barrier, with an R + C value of 5.3177 and an R–C value of 6.1692. This barrier is part of the cause group, but placed at a level influencing first and second-level barriers. This finding aligns with that of Kouhizadeh et al. (2021), who explained that BLC is immature still, making the data handling capabilities a significant issue for integrating it with other technologies such as IoT. Saadatmand and Daim (2019) also emphasized upon the scalability issues that need to be improved with the increasing number of transactions. The "**lack of data regulation**" is part of the effect group driven by high investment cost, lack of government regulation, and low competency of workers. Astill et al. (2019) as well pointed out the importance of developing an efficient strategy for data sharing and data access to provide more security and build trust among stakeholders. Saadatmand and Daim (2019) pointed out that BLC and IoT, as data-driven technologies, need more effective data regulation for secure and transparent data transfer between devices.

Further, the performance of the technology-enabled supply chain will depend upon the way data was collected, stored, and accessed. Inadequate rules and regulations and "**lack of industry standards"** of using data and technologies have strengthened some barriers such as "**lack of trust and privacy.**" This finding is in line with the outcome of Aaldering and Song (2020), who mentioned that since there is no universal or consistent plan for incorporating digital technologies and as an organization is using this as per their requirements, there is a need for a well-defined framework or methods to address BLC-IoT, adoption process, or transformation stages to build safety and reliability. Daim et al. (2013) pointed out the significance of protecting personal and organizational information while technologies such as BLC and IoT use cloud-based storage systems to store data.

An additional finding is that the **lack of resources** (AT-1) is also a significant barrier in the implementation process of BLC-IoT, even if it is surprisingly not the most important one in the area of FSC. This finding

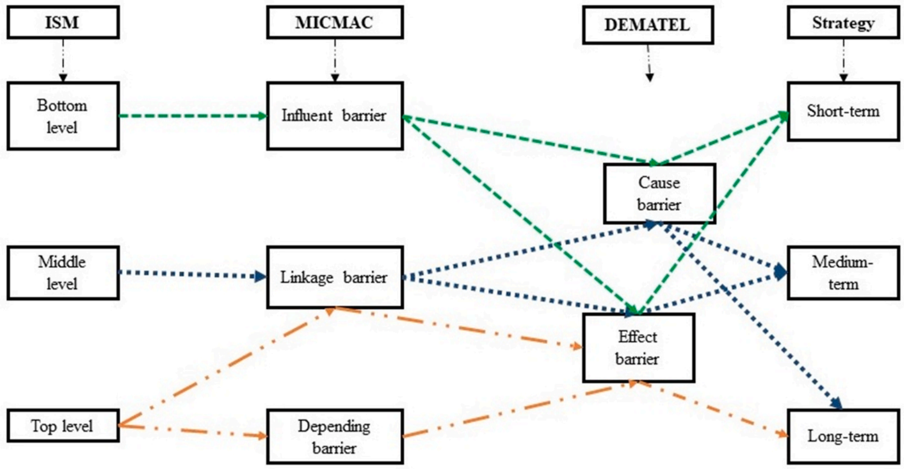

Fig. 5. Different strategies for implementing IoT-BLC in FSC.

is in line with Delgosha et al. (2021), who explain that IoT devices require many resources to detect, transmit, and compute information correctly. The effective operation of an IoT device, balancing of sensor load, frequent verification of sensor robustness, and coverage require additional resources and expenses (Alzahrani and Daim, 2022).

From the societal and the human point of view, the behavioral aspect is found in the barriers "**lack of public awareness"** and **"low attitude towards adoption"**, which are placed at the second level in the ISM hierarchy. Indeed, it is critical to raise awareness to boost engagement and commitment, promote self-mobilization and effort, and utilize local expertise and resources for technology utilization and adoption. The lack of public awareness is part of the cause group, driving the low attitude of adoption. This outcome is backed by Lavoie et al. (2020), who stated that sufficient knowledge and awareness of technologies are required for efficient technology transfer or new technology deployment. Finally, the barrier "**high time for finality settlement"** (AT-6) is driven by all the barriers, as shown in Fig. 3. This barrier is related to delay in payment due to limited consensus protocol, smaller nodes, and legal procedures, which are also addressed by (Viriyasitavat et al., 2019).

6. Conclusion

This paper analyzes the adoption barriers against integrated BLC-IoT and their cause-effect relations in the Indian food supply chain. It, therefore, moves away from other research works analyzing these technologies independently. The 13 barriers identified from the literature and validated by Indian experts were examined using an integrated ISM-DEMATEL approach. The study's outcome revealed that "lack of government regulation" and "low competency of workers" are the most critical barriers restricting the utilization of the BLC-IoT system in the FSC. The study also identified lack of resources, lack of public awareness, high investment cost, and lack of scalability and interpretability as significant barriers for the adoption of BLC-IoT.

Managerial and practical contribution.

This study contributes to the existing literature by identifying 13 critical barriers for BLC-IoT adoption. The findings of this study highlighted the growing problems in adopting BLC-IoT in FSC for improving food quality and safety. This study will direct professionals in developing strategies for technology transfer and adoption. The 13 barriers can be used to develop three types of adoption strategies by considering different sets of barriers at different levels, as shown in Fig. 5.

The barriers at the bottom level of the ISM model, i.e., lack of government regulation (AT-5) and low competency of workers (AT-12), must be considered for short-term strategy. The barriers AT-5 and AT-12, constituting the model's foundation, fall in an independent cluster, where the high R–C values make them more critical than other barriers. It is essential to review, reinforce, or scrap the existing government rules and regulations to support or promote a digital environment for enhancing food quality and safety in FSC. The authorities (government and organization) should start or at least promote skill improvement programs for employees in the food industry (supervisors, managers, and executives) to develop adequate skills needed to address modern technologies.

The middle-level barriers are driven by bottom-level barriers that need to be considered in medium- and long-term strategies. An organization needs to consider the barriers under the cause groups (lack of resources (AT-1), high investment cost (AT-4), lack of scalability and interoperability (AT-13)) for medium-term strategy. They also need to consider lack of trust (AT-3), lack of industry standards (AT-7), lack of infrastructure (AT-8), and lack of data regulation (AT-9). They are part of the effect group, for long term strategy. As the barriers considered under this strategy are part of linkage, policymakers need to put more effort and attention while making decisions. Lack of public awareness (AT-2) and poor attitude towards adoption (AT-10) are barriers related to behavioral aspects that would take time to change. This can be improved by making sure that information and knowledge are publicly available. Making documentation and applicable regulations publicly available will reduce administration expenses, encourage internal cooperation among governmental departments, and allow third-party providers to make this evidence readily accessible for stakeholders in the food supply chain. The barriers at the top of the ISM model (high time for finality settlement (AT-6), lack of public awareness (AT-2), and low attitude towards adoption (AT-10)) are part of low R–C value (effect group), linkage, and dependent cluster. As others drive these barriers, reducing the impact on the adoption process depends upon eliminating the cause barriers. Hence, these barriers should be considered for long-term strategy.

The current study can expand previous research considerably, but it does have some limitations. Indeed, the outcome of this study is valid for the food supply chain sector and cannot be generalized for other sectors without modifications. Furthermore, the selection of barriers and the analysis are based on expert opinions that are not only context-dependent but depend also on their organization's culture and experience. Therefore, the relations established among barriers might be biased (Kumar et al., 2021a,b). This research work can be extended from the Indian context to a wider coverage by selecting experts from different countries for benchmarking studies. In addition, future work can use analytical methods to remove the unavoidable biases of the present study and to check the performance trade-off with proposed technological implementations. .

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