Journal of Global Information Management
Volume 31 • Issue 7

A Decision Framework for Assessing and Improving the Barriers of Blockchain Technology Adoption

Fu-Hsiang Chen, Chinese Culture University, Taiwan

Kuang-Hua Hu, Nanfang College Guangzhou, China

Sin-Jin Lin, National Kaohsiung University of Science and Technology, Taiwan*

Ming-Fu Hsu, National United University, Taiwan

ABSTRACT

Blockchain is regarded as a mainstream technology by corporate leaders, who believe it will drive a new generation of business models. The trends of digital innovation have accelerated corporate blockchain technology adoptions, but when it comes to its applications, numerous barriers still exist that must be carefully addressed. In contrast to past decades, data gathering with the help of information technology has switched from being an expensive to an inexpensive process. It brings users sufficient messages, but also incurs the information overload problem. To combat this, a fusion framework integrated FRST-PSO and fuzzy DEMATEL is introduced herein. It assists users in identifying essential information and depicting the opaque relationships among criteria. The findings indicate that improvement priority, which runs in the order of regulatory environment, blockchain development talent, system integration, and function and reliability based on the magnitude of the impact, serves as a reference for the blockchain technology adoption to facilitate/solidify a firm's competitive edges.

KEYWORDS

Blockchain Technology, Fuzzy Rough Set Theory, Manufacturing, Multiple Criteria Decision-Making, Operation Management

INTRODUCTION

Industry 4.0 is revolutionizing the manufacturing processes, quality improvements, and product distributions of companies (Leng et al., 2020). It helps enhance automation performance, predictive maintenance, and dynamic process improvement and most importantly provides a higher level of efficiency and increases a firm's reaction to customers. While Industry 4.0 involves huge amounts of industrial data and information security issues, the emergence of blockchain with its advantages of immutability, decentralization, and automation has accelerated the realization of the smart factory and has become an emerging driver for economic development in the new era (Bolek et al., 2023; Hughes et al., 2019; Zuo, 2020). Weill and Woerner (2018) also indicated that this new technology

DOI: 10.4018/JGIM.330134 *Corresponding Author

can make corporations be more ready for future markets and strengthen their profitability by 16% in contrast to traditional corporates. This technology has drawn the widespread interest of businesses since 2009, and an excellent and full discussion of it appears in the literature (Luthra et al., 2022; Singla et al., 2023; Vincent et al., 2020; Yadav et al., 2020).

In the digital era, blockchain development is shifting from initial introduction and in-depth exploration to practical application today. The characteristics and advantages of blockchain appear to be more entrenched and have attracted entities around the world to jump into the torrent of related technology. As business executives see the potential and benefits of blockchain for business operation management, its adoption is inevitable (Pawczuk et al., 2019), and it also is a key competitive edge in today's modern business world. Various organizations are investing more resources into setting up blockchain-based systems to accelerate their operation efficiency as well as capture new profit streams (Pawczuk et al., 2018).

The adoption and implementation of blockchain-enled systems have shown some progress in the real world in recent years (Pawczuk et al., 2020). At the same time, the adoption of blockchain is fundamentally changing as well as revolutionizing the entire corporate world. The field of enterprise operation management in the manufacturing industry involves diverse areas, such as production, manufacturing, and service (Hortovanyi et al., 2021; Khayer et al., 2020; Meredith et al., 1989). In today's digital settings, internal and external environments have become more complex, making it hard for existing operation models to achieve the goal of comprehensive management (Lamba & Singh, 2017) – that is, traditional models cannot depict the full picture of a corporate's operation status. Thus, there is an urgent requirement to realize how to create a safe, private, and reliable work environment for corporates. The unique capabilities of blockchain provide an effective solution for massive datasets generated from multiple sources in real time. Enterprises are thus importing blockchain technology into legacy systems to conduct effective operation management (Lohmer & Lasch, 2020). At the same time, blockchain is triggering a destructive business model for manufacturing enterprises that implement the technology.

Although blockchain is a promising tool across a variety of industries, in practice this technology, like any potentially disruptive system or architecture, faces a number of challenges, obstacles, and barriers in terms of adoption and implementation (Biswas & Gupta, 2019; Li et al., 2021) for a firm's daily operation. Corporates looking to digitally transform must determine how best they fit into the integration of blockchain technology and re-establish their operating strategy via an emerging more advanced way of doing business (Berman, 2012). However, research studies on blockchain-based operation management in manufacturing industries are still rare and in the infancy stage (Biawas & Gupta, 2019; Lohmer & Lasch, 2020). As such, it is indispensable for empirical evidence to determine and identify obstacles and problems before creating an enterprise blockchain platform (Tao et al., 2022; Yadav et al., 2022). Doing so will be beneficial to decision-makers and assist at eliminating the major barriers during the efficient implementation of blockchain-based technology; it will also alleviate any implementation failures and risks after adoption.

To the best of the authors' knowledge, there is no systematic and comprehensive review of studies on the integration of artificial intelligence (AI) and multiple criteria decision-making (MCDM) for identifying the barriers of blockchain technology adoption in the operation management sector in China's manufacturing industry. The authors' research work contributes to the operations management field by filling this gap through a critical and rigorous evaluation of such studies. The three principal questions the study aim to address are:

Q1: What are the critical barriers to blockchain technology adoption in China's manufacturing industry?
Q2: How are these barriers prioritized in China's manufacturing industry?
Q3: How do critical barriers assist in validating blockchain technology adoption in China's manufacturing industry?

This research work concentrates on two core elements: 1) identifying the most influential barriers to blockchain technology adoption in China's manufacturing industry; and 2) initiating an action plan framework for blockchain validation in China's manufacturing industry. This research work contributes to the literature on the field of blockchain technology adoption and MCDM through the following ways:

1. Introduces an innovative fusion architecture that integrates AI and MCDM for evaluating barriers to blockchain technology adoption in China's manufacturing industry.
2. Conventional rough set theory (RST) only accepts discrete data that go through a discretization procedure that will lead to information loss. The discrete data also cannot fully capture imprecise characteristics. To handle such challenges, the fuzzy set theory (FST) is integrated into RST (herein, fuzzy rough set theory, FRST) to equip the model (FRST) with higher flexibility and superior tolerance.
3. The model with explanation capability facilitates the realization of its judgments for users, removes the resistance of black-box model execution, and broadens its practical application. The decision logics derived from FRST can be represented in an "if-then" format that is widely welcomed in the decision-making field with greater comprehensibility. Decision makers can examine the logics embedded in FRST to confirm the effectiveness or preciseness of the concluding result as well as increase users' confidence when they reach their final judgments.
4. The best reduct (that is, the most essential feature subset) determination for FRST requires considerable amount of computational cost, when the input data proliferate dramatically. To combat this, particle swarm optimization (PSO) (one type of swarm intelligence approach) with superior searching capability is adopted to look for a solution that is very close to the optimal solution. It requires extremely fewer efforts as well as speeds up the decision-making process in identifying essential barriers of blockchain technology adoption. This advantage fits quite well in today's big data environment.
5. The inherent relationships among barriers are quite obscure and complex. DEMATEL with its ease-of-use and greater interpretation ability is widely adopted to depict the cause-and-effect relationship among barriers. Fuzzy DEMATEL (herein, FDEMATEL) is upgraded from the conventional DEMATEL by considering the fuzzy number interval, providing flexibility in the decision model and yielding much more in-depth insights.
6. Through joint utilization of FRST-PSO and FDEMATEL, the authors propose an action plan framework for blockchain technology adoption validation in China's manufacturing industry as well as help decision makers/top managers deploy limited resources to suitable places with fewer risk exposures.

The rest of the study is constructed as follows. The first section reviews the literature relating to potential barriers of blockchain adoption in manufacturing. The next section describes the proposed methodology. The following section analyzes the data collection processes and empirical results. The next section demonstrates the discussion and theoretical contributions. The final section concludes the research and presents some limitations.

LITERATURE REVIEW

This section presents a systematic literature review of the evaluation framework on the barriers of blockchain adoption operation management in the manufacturing industry. Following the extant literature, practical requirements and suggestions are provided for an evaluation framework of the barriers (determinants) of blockchain technology adoption in this industry. A brief tour of the proposed dimensions is addressed as follows.

Barriers to Blockchain Technology Adoption

Based on the literature review on the barriers to blockchain technology adoption, the authors set up four main groups for discussion: system integration, function and reliability, blockchain development talent, and regulatory environment.

System Integration

The integration of blockchain technology with existing working systems is the most important barrier (Ghobakhloo, 2018). Many organizations around the world contemplating blockchain-based applications do so in response to the current information environment and to improve operational performance without fully replacing their existing systems (Prewett et al., 2020). Hence, a customized solution needs to be developed to integrate the new technology and legacy system, thereby requiring suitable application programming interface (API) gateways to reconcile incompatible issues (Kim et al., 2019). During the integration process of the old and new systems, existing systems are likely to be forced to shut down, incurring time and money costs. The high replacement cost from incorporating new technologies represents a primary impediment for the adoption of potential blockchain for corporates (O'Dair & Owen, 2019). In addition, multiple blockchains from various blockchain software systems/providers need to address interface interoperability and data integration for achieving data sharing and exchange (Carvalho et al., 2021) as well as to protect data security.

Function and Reliability

A novel technology like blockchain is an unfamiliar area for most users in manufacturing industrial operations (Vafadarnikjoo et al., 2021). This point is crucial when they encounter dramatic organizational change. Unlike traditional application software and operating systems, blockchain suffers from severe technology challenges. For example, the protocol updates for blockchain are unable to roll seamlessly due to the presence of a software bug or because of inconsistencies in the blocks of specific users that may compel the entire blockchain to split unnecessarily or to lose its function. As this emerging technology is unproven and its reliability and functionality are questionable, users do not have the temerity to execute and adopt it. Scalability constraints of blockchain systems in general and the speed of transmission information in particular make it difficult to extend their scope of application (Khan et al., 2020). Tian et al. (2019) suggested that the scalability issue needs to be overcome when adopting a mixed blockchain system. With the number of users, blockchain consortia have sprung up to meet the question of how strong is the demand across global markets (Schatsky & Dongre, 2018). For firms, the choice of a consortium is another problem for blockchain adoption, because improper participation may prompt more intractable problems (Bhatt et al., 2021). Furthermore, blockchain enables partners to share information with each other, thus hardly ensuring the privacy of information. According to a survey (Mishra & Venkatesan, 2021), more than half of employees are worried about the exposure of sensitive information, which leads to potential safety hazards.

Blockchain Development Talent

The evolution and development of blockchain-based applications are disrupting the traditional operation model in entire businesses, and the corresponding demand for professional talents has increased significantly. However, current employees lack the necessary skills and competencies when corporates adopt this emerging technology (Clohessy & Acton, 2019). Staff education and training cannot meet the quantitative and qualitative needs of enterprise transformation over a short period of time. Thus, the recruitment of qualified technical personnel is one of the important channels to bridge the talent gap (Mishra & Venkatesan, 2021). With the shortage of high-skilled talents in the market, a firm's recruitment plans and recruitment strategies are often not as good as expected. Moreover, senior executives of some companies do not understand what blockchain is, how it works, and what the real returns are for a new technology import in their firm. They tend to prioritize improvements in existing equipment and are stuck in traditional operational management practices (Sáez, 2020).

Regulatory Environment

The regulatory environment, with its high complexity involving regulations, jurisdictions, and tax laws, is a big impediment to corporates for realizing blockchain technology (Low & Mik, 2020). Since blockchain distributed ledgers that provide nodes could be in a different region or country, it is still impossible to find an appropriate solution to resolve the potential conflict on a blockchain-based platform (Mathivathanan et al., 2021; Wiatt, 2019). Transaction friction is unavoidable on blockchain systems, as users are scarcely protected from accidental loss or damage across different legal regimes. If a dispute occurs, then the parties are outside of the jurisdiction, and the law could be powerless to arbitrate this incident or even exact punishment (Low & Mik, 2020). Current laws and regulations on blockchain systems for most entities are absent and incomplete. How to integrate new rules on blockchain systems into legacy regulations is an urgent issue for companies; however, there seems to be no effective initiative. Regulations and policies that cannot keep pace with blockchain development are important determinants of adoption impediments (Tseng & Shang, 2021; Luthra et al., 2022).

Blockchain Technology Adoption in Manufacturing

Relying on advanced cryptography, blockchain works as an open-source distributed database (Kirkland & Tapscott, 2016) that allows participants to modify/change the underlying code, yielding an opportunity for them to see what is actually happening (Akter et al., 2022). The blockchain platform is a true peer-to-peer (P2P) architecture that does not need intermediaries to authenticate or settle transactions. This disruptive technology is tamper-resistant and can dramatically reduce operation costs, such as the expenditure of verifying the detail of each business transaction and the expense on intermediaries (Michelman, 2017). Babich and Hilary (2020) identified five core advantages of executing blockchain technology in business operations: visibility, aggregation, validation, automation, and resiliency. It is popularly adopted in management applications (Tandon et al., 2021), healthcare applications (Tandon et al., 2020), and natural resource utilization (Saberi et al., 2019a). It is also broadly executed in supply chains (SC) to decentralization, trust, and visibility (Rogerson & Parry, 2020). It not only can transmit information among SC partners effectively, but can also provide data transparency to customers (Cole et al., 2019). Kumar et al. (2020) argued that blockchain technology can be viewed as a "silver bullet" for SC, because it can facilitate collaboration, accountability, anonymity, persistence, and transparency. Even though blockchain technology can bring many advantages, it is still in the early stage of development and needs to address a number of technical, sector-related, and human-related challenges (Wang et al., 2016). Thus, there is an urgent requirement to identify the barriers of blockchain technology adoption to keep pace with the current development of digital transformation.

The Hybrid Methodology

Although the literature presents a considerable amount of dissimilar barriers to blockchain technology implementation, research works still lack substantive and comprehensive analysis of the barriers associated with these individual challenges/obstacles and how they could be associated with each other within a generic architecture depicting interdependency (Rana et al., 2022). Biswas and Gupta (2019) also indicated that existing works seldom rank the barriers according to their essence, identified the causality relations among them, and proposed an appropriate strategy to deploy resources to suitable places to keep up with the evolving digitalization trend. Therefore, it becomes imperative to engage in developing sophisticated MCDM algorithms and to examine the barriers that can help consider dissimilar types of trade-offs and contradictory objectives. Among current MCDM algorithms, analytical hierarchy process (AHP) and interpretive structural modelling (ISM) are widely executed by decision-makers. Recently, diverse studies have demonstrated that DEMATEL and ISM perform better than AHP when it comes to examining mutual dependent criteria. Furthermore, the DEMATEL technique can point out the total degree of influence for each criterion, and hence decision-makers consider it superior to ISM-based algorithms (Gabus & Fontela, 1972). Lee et al. (2013) also indicated that the result derived from DEMATEL is robust even when the sample size of experts is limited.

For an unfamiliar domain, users tend to collect information as much as possible to infer the real situation they face. However, not all of the collected information is useful (that is, some information may be contaminated by some degree of errors), and too much information will confuse decision-makers' judgment. To alleviate the information overload problem and fit properly into the big data era, feature selection aims at identifying essential features without impeding the model's effectiveness. Moreover, in contrast to related works that focus heavily on a single structure (i.e., MCDM only and AI only), this study, inspired by ensemble learning that complements the error made by a single structure, borrows the advantages from AI and MCDM to form a fusion model to identify the essential barriers of blockchain technology adoption. Via advanced hybrid model establishment, decision-makers can gain much deeper insights as well as minimize the risk exposure they face. Table 1 presents the barriers to blockchain technology adoption in manufacturing and the works where they are referenced.

METHODOLOGY

A blockchain literature review reveals that many scholarly studies have overlooked a detailed discussion on the barriers that may impede its successful adoption and implementation in industrial areas. Moreover, academia and practice have concentrated more on cryptocurrencies, but not on the obstacles faced when putting blockchain into real-life practice. Hsieh and Brennan (2022) and Ren

Table 1. Barriers to blockchain adoption

Barriers	Reference
API (application programming interface) gateway	Kim et al. (2019)
Data security	Biswas and Gupta (2019)
Data share and exchange	Carvalho et al. (2021)
Data integration	Saberi et al. (2019a)
High cost	O'Dair and Owen (2019)
Technology is unproven	Biswas and Gupta (2019)
Scalability	Tian et al. (2019); Khan et al. (2020)
Blockchain consortium	Schatsky and Dongre (2018)
Sensitivity of competitive information	Mishra and Venkatesan (2021)
Blockchain-based skills and competencies	Clohessy and Acton (2019)
Employee blockchain knowledge	Saberi et al. (2019b)
Recruitment of qualified technical personnel	Mishra and Venkatesan (2021)
Executives' cognition	Sáez (2020)
Intellectual property	Saberi et al. (2019b)
Jurisdictions	Low and Mik (2020)
Data privacy	Swan (2015)
Enforceability of contracts	Saberi et al. (2019a); Akter et al. (2022)
Current regulation	Tseng and Shang (2021)

et al. (2022), for example, analyzed the risks and issues that are highly relevant to cryptocurrencies. Biswas and Gupta (2019) and Vafadarnikjoo et al. (2021) raised pertinent questions about the potential risks or obstacles for blockchain adoption. However, the authors find that the literature lacks a single, well-developed overarching study that points out the major barriers to blockchain adoption, prioritizes them based on their essence, exploits the inherent opaque cause-and-effect relations, and finally concludes with recommendations that can be further taken as a navigator to escape from the adoption risks/failures (Akter et al., 2022; Biswas & Gupta 2019).

Barrier analysis in the context of practical application is a complicated problem to deal with, and when barriers are large in number, intricate interactions exist between them. Therefore, it is an urgent task to engage in developing an advanced model that not only eliminates the influence of information overload, but also determines the most essential barriers by considering the trade-off and contradiction among them. To combat the aforementioned challenges and fill the research gap, the integrated research framework, as seen in Figure 1, introduces two essential processes: (1) critical criteria exploitation by using FRST with PSO, and (2) depiction/visualization of causal relationships via fuzzy DEMATEL. Each process is described as follows.

1. To make the problem more comprehensible and easier to follow, it is essential to determine potential criteria/dimensions and to distribute/group them into a hierarchical structure. For an unfamiliar domain, decision-makers tend to collect as many messages as possible to infer the inherent situation of the environment. However, too many criteria for decision-makers not only could result in misunderstanding or biased judgments, but could also make it complicated for them to do a pairwise comparison and to obtain a consensus outcome. From the viewpoint of knowledge induction, some collected criteria can be insufficient or redundant. Thus, the core question is how to determine the relevant criteria to obtain knowledge stored in data (Liu & Motoda, 2007) to gain a better understanding of them and to strengthen the prediction performance of the model.

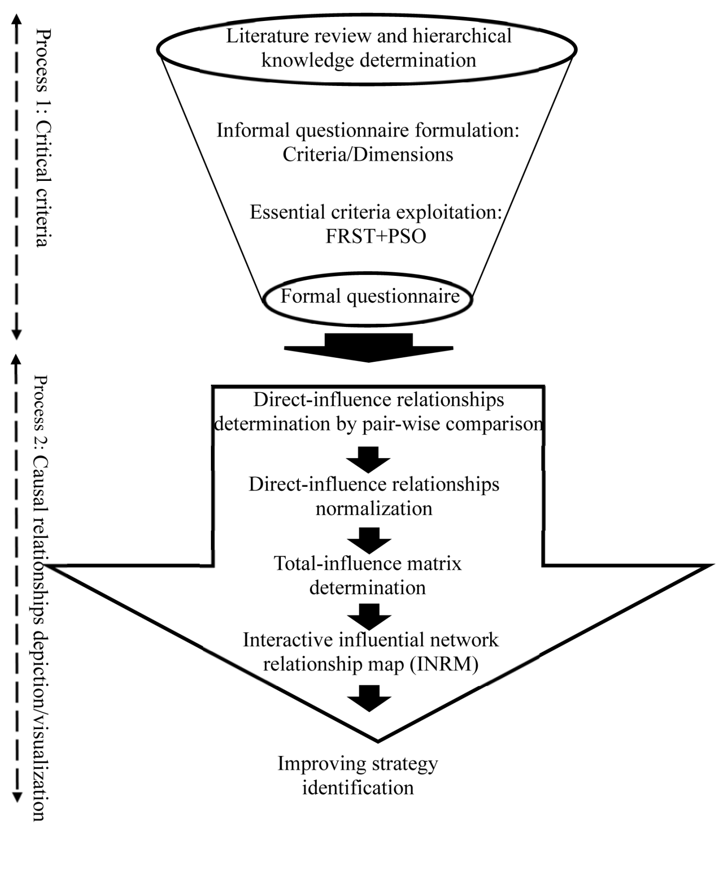
Granular computing is a new computational avenue grounded on knowledge exploitation and reasoning with information granules (Zadeh, 1997) that have caught considerable attention in the fields of data mining and machine learning (Abedin et al., 2023; Alon et al., 2023). The two most representative avenues are rough set theory (RST) and fuzzy set theory (FST). The former, based on mathematics, depicts indiscernibility between dissimilar elements in a set through a series of equivalence classes (Pawlak, 1982), and the latter considers the membership function to describe the degree to which an element belongs to a specific subset. Even though RST has numerous advantages to handle data with uncertainty caused by indiscernibility, when it comes to handling incomplete data it cannot reach a satisfactory outcome. To combat this, the fuzzy rough set theory (FRST) takes advantage of FST to consider the vagueness (Ding et al., 2020; Qian et al., 2017) and incorporate it into RST so as to cope with incomplete information (Radzikowska & Kerre, 2002). This integration has shown promising performance in knowledge exploitation, dimensionality reduction, and intelligent perception (Hsu et al., 2022; Hu et al., 2011).

In FRST a fuzzy relation is adopted to describe the degree of relationship between two elements. The fuzzy-rough lower and upper approximations approximate the fuzzy sets with fuzzy relations. Therefore, the elements in a set are discernible from each other to a specific extent rather than being indiscernible (Ding et al., 2020). With ever-increasing data dimensionality and complexity, FRST appears much more suitable to fit into most business environments due to its higher flexibility (Dubois & Prade, 1980; Dubois & Prade, 1990). Moreover, explanation/interpretability is one of the most essential issues that have gained broadly attention, not only in philosophy, but also in the field of decision-making and AI (Friedman, 1974). Since the early development of decision support systems (DSS) and following by case-based reasoning (CBR), explanation is still at the top rank that affects the acceptance rate of these techniques by end-users (Barakat & Bradley, 2010). In the same vein, it has also been shown that the explanation of outcomes derived from AI algorithms is a vital judgment for the acceptance of black-box algorithms by end-users. The knowledge generated from FRST can be represented in an "if-then" format that poses many advantages, such as its being easy-to-grasp, intuitive, and a less cognitive burden, as mentioned by Karthik Chandra et al. (2009). Users can examine the decision logics embedded in FRST so as to reach a solidified judgment.

The optimal reduct decided by FRST reaches outstanding performance, but its calculation complexity is extremely high, especially when the variable increases exponentially. This is because the optimal reduct is decided after considering all possible generated reducts, and it is the only avenue to conclude the outcome. Skowron and Rauszer (1992) stated that the best reduct determination is an NP-hard task. To combat this, several investigated aspects have utilized meta-heuristic algorithms, such as genetic algorithm (GA), particle swarm optimization (PSO) etc., for near-optimal reduct computation (Jensen et al., 2014) so as to alleviate computational burden and to maintain similar computational performance to the optimal configuration. In contrast to GA, PSO offers a faster convergence rate and higher scalability (Chityal & Sapkal, 2022). Thus, this study takes PSO as a remedy for handling the optimization task for FRST (herein, FRST-PSO), as seen in Appendix A, and adopts this hybrid approach to preliminarily screen essential and information-contained factors/criteria.

2. After exploiting the essential factors (barriers) by FRST-PSO, the authors further analyze the inherent correlations among barriers to the adoption of blockchain technology by DEMATEL in order to gain greater in-depth insights. In contrast to probability theories, DEMATEL is

Figure 1. The flowchart of the introduced hybrid model



theory-oriented without extensive data gathering and can display contextual relations between analyzed factors and represent them via matrices and graphs with higher interpretation ability (Asadi et al., 2022). Due to these advantages, it has been broadly executed in many domains with admirable successes (Rodrigues et al., 2022). However, domain experts have a hard time describing the correlations between factors quantitatively. For this purpose, since it is complicated to decide the degree of interaction between factors, fuzzy DEMATEL (herein, FDEMATEL), as seen in Appendix B, has been introduced to cope with this challenge (Jeng & Tzeng, 2012). In FDEMATEL, a multiple pairwise comparison helps generate the fuzzy direct-influence matrix and then normalizes it so as to lower the variance among factors. All the rows and columns are summarized from a normalized fuzzy direct-influence matrix for building a fuzzy total-influence matrix. INRM thus forms a picture in which decision-makers clearly recognize those barriers greatly impacting blockchain technology adoption.

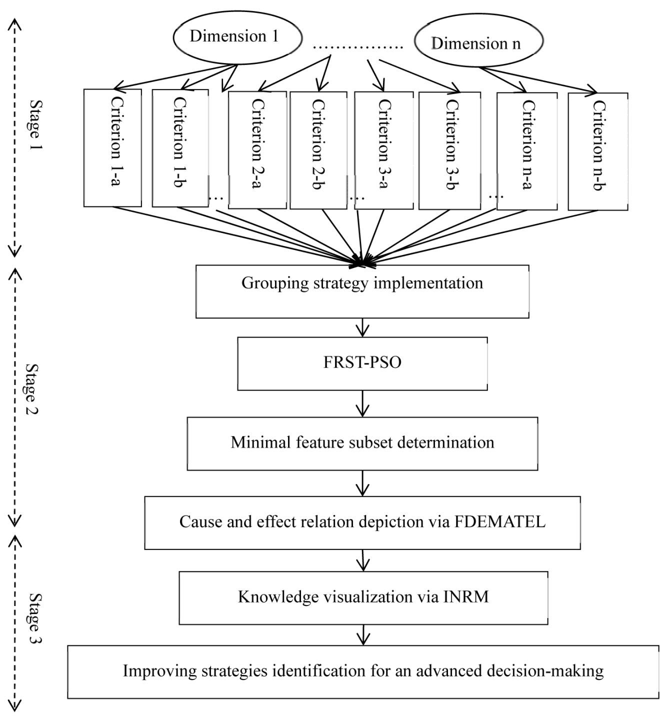
ANALYSIS OF RESULTS

The authors divide this analysis into two parts: (1) data collection and questionnaire development process, and (2) how to construct INRM using the FDEMATEL technique, based on the results of expert knowledge.

Data Collection and Questionnaire Development Process

The questionnaire development process in this study involves the following three stages, as seen in Figure 2 and Appendix C. First, the authors identify these barriers with the help of an extensive literature review (Biswas & Gupta, 2019; Ghobakhloo, 2018; Low & Mik, 2020; Luthra et al., 2022; Pawczuk et al., 2018; Prewett et al., 2020; Yadav et al., 2022) on barriers of blockchain adoption for

Figure 2. The architecture of a three-stage questionnaire development



operation management and domain experts' brainstorming and opinions. The authors then organize them into a hierarchical structure that consists of four dimensions and 18 criteria for a preliminary questionnaire, as seen in Table 2.

Second, the authors distributed questionnaires to all the 55 identified domain experts, asking for their consent for participation (this is the authors' first round of experts' opinion collection). Consents from 16 experts working for 13 companies in Guangzhou and Shenzhen were received, either verbally or written, resulting in a response rate of 29.10%. Among the 16 experts, as seen in Table 3, eight are general managers or factory managers in Guangzhou's or Shenzhen's major manufacturing companies, and eight are senior engineers with blockchain experience in Guangzhou's or Shenzhen's major manufacturing companies. They were invited to score the preliminary questionnaire from 0 (low) to 10 (high) to indicate the importance of all criteria. The duration of interviews varied from 25 to 72 minutes and averaged 43 minutes. The interviews were conducted from January 2021 to March 2021.

The class label must be decided beforehand and then execute FRST-PSO hybrid technologies for screening the key elements. The *K*-means algorithm based on Thangavel et al. (2005) is a promising means to decide the class label. The aggregation of forecasting preciseness and rule coverage (AFPRC) serves as an evaluation benchmark. To clarify that PSO has good searching capability, this study takes it as a benchmark and compares it with the other three meta-heuristic algorithms, such as genetic algorithm (GA), ant colony optimization (ACO), and greedy search (GS). Table 4 shows that FRST with PSO poses superior performance. From the result, 11 key criteria are left over from 18 criteria, as seen in Tables 5-6. To prove the FRST-PSO technology has the merit of higher interpretability that surpasses other methods, the Friedman test is used to implement this task. The results appear in Table 7. Here, FRST-PSO not only has good discriminant capability, but also possesses higher interpretation capability. Due to these two merits, FRST-PSO is aptly suited for helping decision-makers to filter

Table 2. Barriers of adoption of blockchain technology for the pre-test questionnaire

Dimensions	Criteria
(A) System integration	c_1: API (application programming interface) gateway
	c_2: Data security
	c_3: Data share and exchange
	c_4: Data integration
	c_5: High cost
(B) Function and reliability	c_6: Technology is unproven
	c_7: Scalability
	c_8: Blockchain consortium
	c_9: Sensitivity of competitive information
(C) Blockchain development talent	c_{10}: Blockchain-based skills and competencies
	c_{11}: Employee blockchain knowledge
	c_{12}: Recruitment of qualified technical personnel
	c_{13}: Executives' cognition
(D) Regulatory environment	c_{14}: Intellectual property
	c_{15}: Jurisdictions
	c_{16}: Data privacy
	c_{17}: Enforceability of contracts
	c_{18}: Current regulation

Table 3. Profile of the domain experts participating in this study

Profile	Industry	Experience (Years)	Blockchain Technology Implementation Domain
1. General Manager	Production	10-15	Supply chain management
2. General Manager	Production	10-15	Spare parts management
3. Factory Manager	Production	15-20	Inventory management
4. General Manager	Manufacturing	10-15	Spare parts management
5. Factory Manager	Manufacturing	10-15	Supply chain management
6. Factory Manager	Manufacturing	10-15	Inventory management
7. Factory Manager	Service	15-20	Customer service
8. Factory Manager	Service	10-15	Asset tracking
9. Engineer	Production	10-15	Supply chain management
10. Engineer	Production	5-10	Spare parts management
11. Engineer	Production	15-20	Payments
12. Engineer	Production	10-15	Asset tracking
13. Engineer	Manufacturing	10-15	Spare parts management
14. Engineer	Manufacturing	5-10	Supply chain management
15. Engineer	Service	10-15	Customer service management
16. Engineer	Service	5-10	Payments

out redundant messages in a big data era and to provide them with sufficient explanation to confirm their final judgments.

Third, the official questionnaire was designed based on the results of FRST-PSO and submitted to 10 general managers, 10 senior engineers, and 12 highly experienced scholars in IT-related departments in Guangzhou and Shenzhen, who have a good grip of the application of blockchain systems in the manufacturing industry (this is the authors' second round of experts' opinion collection). Each survey questionnaire between April 2021 and June 2021 took about 90 minutes through face-to-face interviews. Experts assessed the influence of each criterion on another criterion with a ranking from 0 to 4, representing no influence and extreme influence, respectively. Finally, all completed questionnaires were input into the FDEMATEL model for further analysis.

Creating INRM Using FDEMATEL

According to FDEMATEL analysis, the fuzzy total influence relation matrix $\tilde{T} = \left(T^l, T^m, T^r\right)$ with T^l, T^m, and T^r correspondingly represents total matrix low, medium, and high can be reached. Subsequently, the fuzzy average total influence relation matrix $\tilde{T}$ is calculated as shown in Table 8. Based on the above results, a cause-and-effect relationship among the elements (barriers) appears in Table 9.

The key cause factors among dimensions with the value of $\tilde{d}_i - \tilde{s}_i$ are positive, including (*D*) regulator environment, which intensely affects other dimensions (Jeng & Tzeng, 2012). This dimension (*D*) acts as an independent variable. This finding supports Charles et al. (2023) and Vafadarnikjoo et al. (2021) who indicated that the most critical hurdle for successful blockchain technology implementation is regulatory environment. The main effect factors among dimensions with the value of $\tilde{d}_i - \tilde{s}_i$ are negative, including (A) system integration, (B) function and reliability, and (C) blockchain development talent, which are intensely affected by the others. These factors are dependent variables.

Table 4. Essential criteria determination by using FRST with dissimilar search methods

Feature Subset	Forecasting Accuracy	Rule Coverage	AFPRC*
Searching method: PSO			
Subset 1: A2, A3, B1, B3, B4, C3, C4, D2, D3, D4, D5	0.87	0.84	1.72
Subset 2: A2, A3, A4, B1, B3, C1, C3, D1, D3, D4, D5	***0.94***	***0.91***	***1.85***
Subset 3: A1, A2, A4, B1, B3, B4, C1, C3, C4, D2, D3, D4	0.88	0.87	1.75
Subset 4: A1, A4, B1, B2, B4, C1, C2, C3, C4, D1, D5, D5	0.90	0.89	1.79
Subset 5: A1, A3, A4, B2, B4, C1, C4, D1, D3, D4, D5	0.86	0.88	1.74
Searching method: GA			
Subset 1: A1, A2, A4, A5, B1, B4, C1, D1, D2, D5	0.82	0.89	1.71
Subset 2: A1, A2, A5, B1, B3, C2, C3, D1, D3	***0.84***	***0.90***	***1.74***
Subset 3: A2, A3, A5, B2, B3, C1, C2, C4, D2, D4	0.85	0.88	1.73
Subset 4: A1, A2, A4, B3, B4, C1, C4, D1, D5	0.81	0.87	1.68
Searching method: ACO			
Subset 1: A2, A4, B1, B2, B4, C2, D2	0.79	0.88	1.67
Subset 2: A1, A3, A5, B2, C1, D1, D3, D4	***0.88***	***0.89***	***1.77***
Subset 3: A3, A4, B1, B3, C2, C3, D5	0.79	0.87	1.66
Subset 4: A1, A2, A5, B3, B4, C4, D1	0.85	0.81	1.66
Subset 5: A1, A3, A4, A5, B4, C3, D3, D5	0.88	0.76	1.64
Subset 6: A1, A2, B3, C1, C2, D2, D5	0.81	0.88	1.69
Searching method: GS			
Subset 1: A1, A3, A5, B1, B3, C2, D1, D4	0.77	0.84	1.61
Subset 2: A1, A3, A4, B2, C1, C3, C4, D3	***0.87***	***0.85***	***1.72***
Subset 3: A1, A2, A4, B3, B4, C4, D1, D2, D5	0.82	0.84	1.66
Subset 4: A3, A4, A5, B1, B4, C1, C3	0.86	0.84	1.70
Subset 5: A2, A3, A5, B2, B3, C2, D2, D4	0.75	0.87	1.62

Note. AFPRC: The aggregation of forecasting preciseness and rule coverage.

Jurisdictions (d_1) is the highest value of $\tilde{d}_i - \tilde{s}_i$ among criteria, representing that this factor is the most influential factor, while sensitivity of competitive information (b_3) and blockchain-based skills and competencies (c_1) have the second and third highest $\tilde{d}_i - \tilde{s}_i$ values, respectively. Similarly, within a separate dimension, API gateway (a_1), sensitivity of competitive information (b_3), blockchain-based skills and competencies (c_1), and jurisdictions (d_1) illustrate the highest values of $\tilde{d}_i - \tilde{s}_i$. To alleviate the cognitive burden of decision-makers, the values on Table 9 can be transformed into an influential network relationship map (INRM), as seen in Figure 3, which speeds up decision-making efficiency.

$$\text{Average gap ratio (\%)} = \frac{1}{n \times \left(n-1\right)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\left| \overline{y}_{ij}^{16} - \overline{y}_{ij}^{15} \right| / \overline{y}_{ij}^{16} \right) \times 100\% = 2.37\% < 5\%$$

Table 5. The criteria adopted in the informal/preliminary questionnaire and formal questionnaire

Dimension	Criteria	(■: Denotes Selected; □: Denotes Not Selected)			
		Preliminary Questionnaire Based on Literature Review		Formal Questionnaire Obtained From FRST-PSO	
		Code	Result	Code	Result
System integration	API (application programming interface) gateway	c_1	■	a_1	■
	Data security	c_2	■	--	□
	Data share and exchange	c_3	■	a_2	■
	Data integration	c_4	■	--	□
	High cost	c_5	■	a_3	■
Function and reliability	Technology is unproven	c_6	■	--	□
	Scalability	c_7	■	b_1	■
	Blockchain consortium	c_8	■	b_2	■
	Sensitivity of competitive information	c_9	■	b_3	■
Blockchain development talent	Blockchain-based skills and competencies	c_{10}	■	c_1	■
	Employee blockchain knowledge	c_{11}	■	--	■
	Recruitment of qualified technical personnel	c_{12}	■	c_2	□
	Executives' cognition	c_{13}	■	c_3	■
Regulatory environment	Intellectual property	c_{14}	■	--	□
	Jurisdictions	c_{15}	■	d_1	■
	Data privacy	c_{16}	■	--	□
	Enforceability of contracts	c_{17}	■	--	□
	Current regulation	c_{18}	■	d_2	■

This result indicates that significant confidence of consensus is 97.63%, where $\bar{y}_{ij}^{15}$ and $\bar{y}_{ij}^{16}$ are the average scores of the experts for 15 and 16, respectively; n is the number of critical criteria (factors) – here $n = 11$ and $n \times n$ matrix.

DISCUSSION

This study explores the potential barriers of blockchain adoption in operation management from domain experts' knowledge, employs FDEMATEL to construct INRM, as seen in Figure 3, and analyzes the causal relationships among systems (dimensions) and sub-systems (factors). After measuring the influential correlation on the barriers of adoption of blockchain technology, the improvement priority for dimensions is (D) regulatory environment, (C) blockchain development talent, (A) system integration, and (B) function and reliability. It is obvious that (D) is the most crucial and direct effect for the influential correlation on other dimensions. If corporates want to adopt blockchain technology in operation management, then they need to give priority to resolving the related problems

Table 6. Adoption of blockchain technology barrier assessment framework

Dimensions/Criteria	Definitions	References
(*A*) System integration		
API gateway (a_1)	Compatibility of new technology and legacy systems as well as system and data integration.	Kim et al. (2019)
Data share and exchange (a_2)	Effective data sharing and exchange is achieved from different sources.	Carvalho et al. (2021)
High cost (a_3)	The high amount of construction funds is required for blockchain introduction.	O'Dair and Owen (2019)
(*B*) Function and reliability		
Scalability (b_1)	The computing capabilities of blockchain technology were used in a wide range and implemented the objectives in a given time period.	Tian et al. (2019); Khan et al. (2020)
Blockchain consortium (b_2)	Different blockchain consortia exists technology difference, and not all consortia can provide a feasible and integrated system.	Schatsky and Dongre (2018)
Sensitivity of competitive information (b_3)	Protection and leakage of sensitive information on the blockchain	Mishra and Venkatesan (2021)
(*C*) Blockchain development talent		
Blockchain-based skills and competencies (c_1)	There is sufficient supply of professionals on blockchain technology	Clohessy and Acton (2019)
Recruitment of qualified technical personnel (c_2)	Whether it is possible to recruit suitable technical personnel	Mishra and Venkatesan (2021)
Executives' cognition (c_3)	Senior executives' knowledge to blockchain	Sáez (2020)
(*D*) Regulatory environment		
Jurisdictions (d_1)	Jurisdiction issues arise from any dispute between blockchain participants	Low and Mik (2020)
Current regulation (d_2)	Existing national legal system related to blockchain	Tseng and Shang (2021)

Table 7. The comparison results (preciseness) (rank)

	The Number of Clusters Were Determined by K-Means			
	K=2	K=3	K=4	K=5
Benchmark: FRST-PSO	94 (1)	86 (1)	82 (1)	76.8 (1)
RST-HC	85.2 (3)	80.4 (4)	74.8 (4)	69.6 (4)
IFWA	84.6 (4)	81.4 (2)	76 (2)	70.6 (3)
DRSA	87.4 (2)	81 (3)	75 (3)	71.6 (2)
Statistical test (p-value)	0.019**	0.008***	0.024**	0.008***

Note. Assessment criterion: preciseness = (true negative + true positive)/(true positive + false positive + false negative + true negative); *, **, *** denotes significance at 10, 5, and 1 percent level of significance.

Table 8. Fuzzy total influence relation matrix $\tilde{T}_a$ for the criteria (average)

Criterion	a_1	a_2	a_3	b_1	b_2	b_3	c_1	c_2	c_3	d_1	d_2
a_1	0.109	0.157	0.157	0.163	0.162	0.145	0.144	0.158	0.154	0.140	0.162
a_2	0.131	0.101	0.136	0.136	0.136	0.122	0.123	0.135	0.133	0.123	0.137
a_3	0.131	0.138	0.104	0.141	0.141	0.133	0.129	0.140	0.143	0.129	0.146
b_1	0.127	0.137	0.134	0.101	0.134	0.123	0.124	0.130	0.130	0.119	0.134
b_2	0.125	0.135	0.134	0.136	0.100	0.127	0.123	0.127	0.126	0.117	0.128
b_3	0.145	0.154	0.154	0.160	0.158	0.108	0.148	0.158	0.152	0.142	0.157
c_1	0.143	0.154	0.146	0.148	0.150	0.139	0.103	0.146	0.146	0.141	0.153
c_2	0.122	0.131	0.131	0.137	0.135	0.127	0.122	0.098	0.126	0.116	0.130
c_3	0.117	0.122	0.127	0.132	0.132	0.119	0.116	0.128	0.095	0.117	0.127
d_1	0.203	0.211	0.207	0.215	0.215	0.201	0.204	0.212	0.210	0.132	0.211
d_2	0.136	0.142	0.142	0.147	0.149	0.139	0.136	0.146	0.146	0.132	0.107

in the regulatory environment. Consistent with Alkhudary et al. (2020), this study indicates that current regulatory frameworks are the chief barriers for blockchain technology implementation. In a similar vein, Millard (2018) argued that the manifested conflict is between blockchain applications and existing legislation, while Luthra et al. (2022) pointed out that the foundation for blockchain technology is to first define standards and regulations.

Providing an appropriate regulatory domain could smoothly enable blockchain technology for enterprises' operation management. Kamilaris et al. (2019) stated that a comprehensive design of a clear regulatory framework is indispensable for lowering the barriers to blockchain adoption. Blockchain technology usage depends on regulatory policies and functions in the manufacturing sector. Crucial to any blockchain requirement framework is how to confirm and clarify domestic and overseas parties' rights and legal liabilities (Gunasekera & Valenzuela, 2020). Cross-border governance of blockchain technology makes it an arduous task to formulate a regulatory structure recognized by all participating entities (Ilbiz & Durst, 2019; Li et al., 2022). To reduce confusion and hesitation and to speed up its utilization in other domains, current regulatory-related rules or principles should be modified and adjusted (Duque & Torres, 2020) to keep pace with the development of blockchain technology. Users can apply the derived outcome to navigate the implementation procedures so as to avoid any disturbances/conflicts in their daily applications.

Table 9. Sum of cause ($\tilde{d}_i$) and effect ($\tilde{s}_i$) relationships of factors

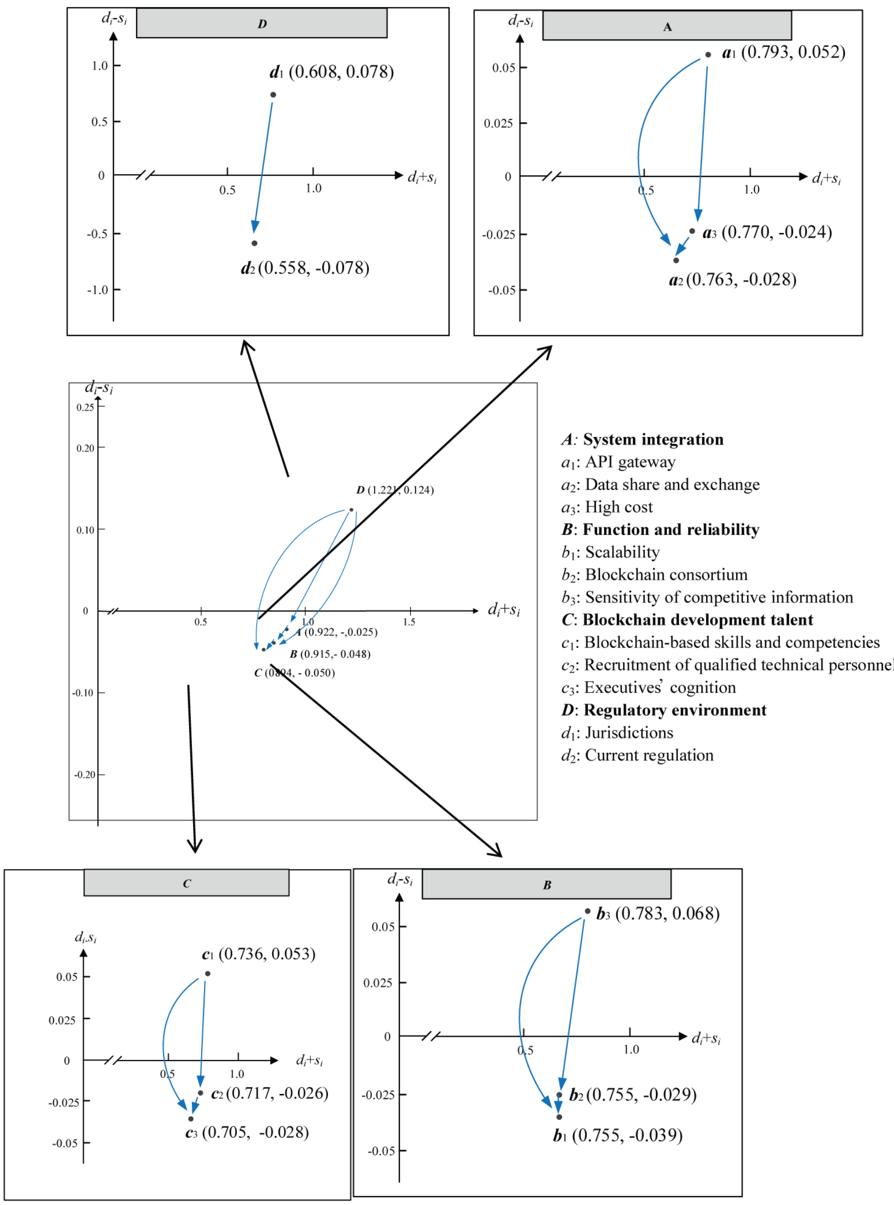
Dimensions/Criteria	Row sum ($\tilde{d}_i$)	Column sum ($\tilde{s}_i$)	$\tilde{d}_i + \tilde{s}_i$	$\tilde{d}_i - \tilde{s}_i$
(A) System integration	**0.448**	**0.473**	**0.922**	**-0.025**
API gateway (a_1)	0.423	0.370	0.793	0.052
Data share and exchange (a_2)	0.368	0.396	0.763	-0.028
High cost (a_3)	0.373	0.397	0.770	-0.024
(B) Function and reliability	**0.434**	**0.482**	**0.915**	**-0.048**
Scalability (b_1)	0.358	0.397	0.755	-0.039
Blockchain consortium (b_2)	0.363	0.392	0.755	-0.029
Sensitivity of competitive information (b_3)	0.426	0.357	0.783	0.068
(C) Blockchain development talent	**1.077**	**1.081**	**2.158**	**-0.004**
Blockchain-based skills and competencies (c_1)	0.395	0.341	0.736	0.053
Recruitment of qualified technical personnel (c_2)	0.346	0.371	0.717	-0.026
Executives' cognition (c_3)	0.339	0.366	0.705	-0.028
(D) Regulatory environment	**0.672**	**0.549**	**1.221**	**0.124**
Jurisdictions (d_1)	0.343	0.265	0.608	0.078
Current regulation (d_2)	0.240	0.318	0.558	-0.078

Theoretical Contributions

This paper offers several theoretical contributions to the extant literature. First, this is a pioneer study as it gathers dissimilar types of blockchain adoption challenges for the manufacturing industry in China along with a review of related studies.

Second, no paper in the area of blockchain adoption barriers has introduced a fusion model that incorporates MCDM and AI to assist decision-makers in formulating a suitable adoption procedure to avoid getting stuck in practical applications. This study is a step forward as it exploits essential criteria from a large amount of data via an AI algorithm. It eliminates the storage requirement, allows users

Figure 3. The INRM of influence relation using FDEMATEL



to concentrate more on specific essential ones, and further depicts the cause-and-effect relationships among criteria and the essence of each criterion via the MCDM approach. In so doing, users can realize the most essential driving challenges as well as other issues dependent on these drivers.

Third, the introduced model can also be extended to other theories. They include group decision-making theory and social network theory of trust. The model can further be incorporated into advanced data extraction techniques, such as text mining and topic modelling. Doing so can help gain more profound messages as well as sustain/improve a firm's competitive advantages.

Implications for Practice and Policy

The fusion architecture introduced herein yields several practical implications for the manufacturing industry in China to smoothly implement and adopt blockchain technology. From the criteria (barriers), experts unanimously agreed that jurisdiction is the biggest obstacle to blockchain use in operation management. This finding validates Rana et al. (2022) and Luthra et al. (2022) who indicated that a lack of standard and a lack of validation are the most essential risks when implementing blockchain technology. A contract usually stipulates the legal governance of a specific country and the exclusive jurisdiction of any disputes based on international legal practice, but it is not applicable in current smart contract settings. The unclear domicile and unclear jurisdiction of smart contracts have caused great difficulties in international supervision (Drummer & Neumann, 2020). Ghode et al. (2020) indicated that blockchain technology is an online and cross-regional system. Given that, there are problems of entity trust and governance among transaction parities due to multiple jurisdictions, and corporates could face new litigation challenges. Existing legal measures of national jurisdiction fail at solving blockchain-based disputes. Many national legal regimes and relevant legislative reforms have not kept up with the pace of blockchain development (Ellul et al., 2020). In the context of a blockchain-based platform, taking into account jurisdiction is a necessary and obligatory measure for cross-border management.

The empirical results also show that sensitivity of competitive information and blockchain-based skills and competencies are the second and third obstacles of adoption, respectively. Although a blockchain system has many superior features such as irreversibility, an inability to be tampered with, and near real-time settlement, it hides the risk of sensitive information leakage when parties' information is exposed to a public network (Cambou et al., 2020). Jo and Choi (2019) suggested that enterprises generally believe that sensitive business information may be shared with any unrelated network participants on an open source system (e.g., blockchain). To smooth users' participation in these blockchain-based platforms, user information and sensitive transaction data must be protected from unauthorized access (Fu et al., 2021). Moreover, developing and maintaining a feasible solution for corporates seems arduous due to a lack of understanding about blockchain technology by existing employees (Daniel & Zhu, 2018). A big concern among senior managers is shortages of related skills (e.g., technological-based skills and business-based skills) (Clohessy et al., 2020) and competencies when contemplating whether to adopt blockchain technology and how to meet future market competition and development (Chillakuri & Attili, 2021). Mathivathanan et al. (2021) noted that business awareness and familiarity with blockchain technology on what it can deliver for corporate future development and their lack thereof are two key barriers hindering its application scale. The above findings offer various suggestions for manufacturing sectors after gaining an overall understanding of the potential barriers of blockchain adoption in operation management.

CONCLUSION

This study applies an integrated methodology, FRST-PSO technology, and FDEMATEL method to manufacturing firms in China to analyze the barriers of blockchain adoption through experts' knowledge. FRST-PSO is used to screen out key factors as well as to eliminate the curse of dimensionality. The FDEMATEL approach is then utilized to support prioritizing these barriers (factors) by considering their interrelationships based on the critical factors. According to the outcome originating from FDEMATEL, the causal relationship among factors can be reached and INRM can be drawn. The findings serve as a reference for senior managers to understand how they should act to minimize these obstacles, to ensure seamless adoption of this disruptive technology in their way of working, and to know what valuable resources and skills are required to overcome the obstacles so as to fully assimilate the adoption of this technology in manufacturing industries at large.

For the dimensions, the importance of the findings can be prioritized as follows: regulatory environment, blockchain development talent, system integration, and function and reliability. Among the criteria, jurisdiction indicates the primary barrier of blockchain technology adoption for manufacturing corporations, and it must first be resolved when moving towards a new system. Given the merit of blockchain technology, corporates should be aware of the fact that, first, they will face considerable changes/modifications in how they function in the following years. Second, similar to prior technological shifts, early movers receive the greatest benefits from it by expanding their business network, establishing standards, and advancing technology execution. However, Akter et al. (2022) indicated that merely holding a powerful and rare IT resource that competitors cannot easily replicate does not necessarily guarantee a competitive edge. He pointed out that the wider concern of risks/obstacles must also be embraced in the strategy paradigm. The proposed hybrid model is satisfactory and can help senior supervisors to realize the risks they face and to then formulate an effective course of action for the avoidance of these barriers.

There are also potential limitations to this research. The invited domain experts may not be comprehensive enough, and there also is a possibility of biased judgments. The sample size is relatively small, which might limit the validity of the empirical findings. A practical evaluation framework could consider other special situations, such as the impact of COVID-19 on this operation model and the division of three different areas (production, manufacturing, and service) in manufacturing industries, or enlarge the sample size in order to examine the influence of barriers in more detail. In the future, other advanced AI algorithms (i.e., incremental filter-wrapper feature subset selection and nearest neighbour-based fuzzy-rough feature selection) (Han et al., 2018; Riaz & Hashmi, 2020) and other sophisticated MCDM approaches (i.e., grey DEMATEL and Pythagorean m-polar fuzzy soft sets, and technique for order of preference by similarity to ideal solution (TOPSIS)) can be executed to rank these barriers with regard to their essence as far as the adoption of blockchain technology is concerned. Finally, this research has also formulated a more focused architecture from the generic viewpoint and formulated propositions between identified criteria. However, this developed architecture has not been validated by the current related studies. The future researchers could operationalize the construct involved in the developed architecture and examine its authenticity.

CONFLICTS OF INTEREST

No conflict of interest exists in this study.

ACKNOWLEDGMENT

The authors would like to thank National Science and Technology Council, Taiwan for financially supporting this project under contracts No. 111-2410-H-239 -010 -MY2; 112-2410-H-992 -061 -MY2; and 112-2410-H-034-014-MY2. The authors also want to thank Department of Education of Guangdong Province, China for financially supporting this project under contract No. 2021ZDJS131.

REFERENCES

Abedin, M. Z., Hajek, P., Sharif, T., Satu, M., & Khan, M. I. (2023). Modelling bank customer behaviour using feature engineering and classification techniques. *Research in International Business and Finance*, *65*, 101913. doi:10.1016/j.ribaf.2023.101913

Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2022). Transforming business using digital innovations: The application of AI, blockchain, cloud and data analytics. *Annals of Operations Research*, *308*(1-2), 7–39. doi:10.1007/s10479-020-03620-w

Alkhudary, R., Brusset, X., & Fenies, P. (2020). Blockchain in general management and economics: A systematic literature review. *European Business Review*, *32*(4), 765–783. doi:10.1108/EBR-11-2019-0297

Alon, I., Bretas, V. P., & Katrih, V. (2023). Predictors of NFT prices: An automated machine learning approach. *Journal of Global Information Management*, *31*(1), 1–18. doi:10.4018/JGIM.317097

Amouzgar, K., Nourmohammad, A., & Ng, A. H. C. (2021). Multi-objective optimisation of tool indexing problem: A mathematical model and a modified genetic algorithm. *International Journal of Production Research*, *59*(12), 3572–3590. doi:10.1080/00207543.2021.1897174

Asadi, S., Nilashi, M., Iranmanesh, M., Ghobakhloo, M., Samad, S., Alghamdi, A., Almulihi, A., & Mohd, S. (2022). Drivers and barriers of electric vehicle usage in Malaysia: A DEMATEL approach. *Resources, Conservation and Recycling*, *177*, 105965. doi:10.1016/j.resconrec.2021.105965

Aydoğan, E. K., Delice, Y., Özcan, U., Gencer, C., & Bali, Ö. (2019). Balancing stochastic U-lines using particle swarm optimization. *Journal of Intelligent Manufacturing*, *30*(1), 97–111. doi:10.1007/s10845-016-1234-x

Babich, V., & Hilary, G. (2020). OM Forum-distributed ledgers and operations: What operations management researchers should know about blockchain technology. *Manufacturing & Service Operations Management*, *22*(2), 223–240. doi:10.1287/msom.2018.0752

Barakat, N., & Bradley, A. P. (2010). Rule extraction from support vector machines: A review. *Neurocomputing*, *74*(1–3), 178–190. doi:10.1016/j.neucom.2010.02.016

Berman, S. J. (2012). Digital transformation opportunities to create new business models. *Strategy and Leadership*, *40*(2), 16–24. doi:10.1108/10878571211209314

Bhatt, P. C., Kumar, V., Lu, T. C., & Daim, T. (2021). Technology convergence assessment: Case of blockchain within the IR 4.0 platform. *Technology in Society*, *67*, 101709. doi:10.1016/j.techsoc.2021.101709

Biswas, B., & Gupta, G. (2019). Analysis of barriers to implement blockchain in industry and service sectors. *Computers & Industrial Engineering*, *136*, 225–241. doi:10.1016/j.cie.2019.07.005

Bolek, V., Romanová, A., & Korček, F. (2023). The information security management systems in e-business. *Journal of Global Information Management*, *31*(1), 1–29. doi:10.4018/JGIM.316833

Cambou, B., Gowanlock, M., Heynssens, J., Jain, S., Philabaum, C., Booher, D., Burke, I., Garrard, J., Telesca, D., & Njilla, L. (2020). Securing additive manufacturing with blockchains and distributed physically unclonable functions. *Cryptography*, *4*(2), 17. doi:10.3390/cryptography4020017

Carvalho, A., Merhout, J. W., Kadiyala, Y., & Bentley, J. I. I. II. (2021). When good blocks go bad: Managing unwanted blockchain data. *International Journal of Information Management*, *57*, 102263. doi:10.1016/j.ijinfomgt.2020.102263

Charles, V., Emrouznejad, A., & Gherman, T. (2023). A critical analysis of the integration of blockchain and artificial intelligence for supply chain. *Annals of Operations Research*, *327*(1), 7–47. Advance online publication. doi:10.1007/s10479-023-05169-w PMID:36718465

Chen, F. H., Hsu, M. F., & Hu, K. H. (2022). Enterprise's internal control for knowledge discovery in a big data environment by an integrated hybrid model. *Information Technology and Management*, *23*(3), 213–231. doi:10.1007/s10799-021-00342-8

Chillakuri, B., & Attili, V. S. P. (2021). Role of blockchain in HR's response to new-normal. *The International Journal of Organizational Analysis*. Advance online publication. doi:10.1108/IJOA-08-2020-2363

Chityal, N., & Sapkal, S. (2022). Performance analysis of GA, PSO and JA for determining the optimal parameters in friction drilling process. *Engineering Science and Technology, an International Journal, 35*, 101246.

Clohessy, T., & Acton, T. (2019). Investigating the influence of organizational factors on blockchain adoption: An innovation theory perspective. *Industrial Management & Data Systems*, *119*(7), 1457–1491. doi:10.1108/IMDS-08-2018-0365

Clohessy, T., Treiblmaier, H., Acton, T., & Rogers, N. (2020). Antecedents of blockchain adoption: An integrative framework. *Strategic Change*, *29*(5), 501–515. doi:10.1002/jsc.2360

Cole, R., Stevenson, M., & Aitken, J. (2019). Blockchain technology: Implications for operations and supply chain management. *Supply Chain Management*, *24*(4), 469–483. doi:10.1108/SCM-09-2018-0309

Daniel, F., & Zhu, L. (2018). Blockchains for business process management – Challenges and opportunities. *ACM Transactions on Management Information Systems*, *9*(1), 1–16. doi:10.1145/3183367

Ding, W., Wang, J., & Wang, J. (2020). Multigranulation consensus fuzzy-rough based attribute reduction. *Knowledge-Based Systems*, *198*, 105945. doi:10.1016/j.knosys.2020.105945

Dou, J., Li, J., Xia, D., & Zhao, X. (2021). A multi-objective particle swarm optimisation for integrated configuration design and scheduling in reconfigurable manufacturing system. *International Journal of Production Research*, *59*(13), 3975–3995. doi:10.1080/00207543.2020.1756507

Drummer, D., & Neumann, D. (2020). Is code law? Current legal and technical adoption issues and remedies for blockchain-enabled smart contracts. *Journal of Information Technology*, *35*(4), 337–360. doi:10.1177/0268396220924669

Dubois, D., & Prade, H. (1980). *Fuzzy sets and systems: Theory and applications*. Academic Press.

Dubois, D., & Prade, H. (1990). Rough fuzzy sets and fuzzy rough sets. *International Journal of General Systems*, *17*(2-3), 191–209. doi:10.1080/03081079008935107

Duque, G. G., & Torres, J. D. Z. (2020). Enhancing e-commerce through blockchain (DLTs): The regulatory paradox for digital governance. *Global Jurist*, *20*(2), 20190049. doi:10.1515/gj-2019-0049

Ellul, J., Galea, J., Ganado, M., McCarthy, S., & Pace, G. J. (2020). Regulating blockchain, DLT and smart contracts: A technology regulator's perspective. *ERA Forum, 21*, 209–220.

Friedman, M. (1974). Explanation and scientific understanding. *The Journal of Philosophy*, *71*(1), 5–19. doi:10.2307/2024924

Fu, Z., Dong, P., Li, S., & Ju, Y. (2021). An intelligent cross-border transaction system based on consortium blockchain: A case study in Shenzhen, China. *PLoS One*, *16*(6), e0252489. doi:10.1371/journal.pone.0252489 PMID:34106969

Gabus, A., & Fontela, E. (1972). *World problem, an invitation to further thought within the framework of DEMATEL*. Battelle Geneva Research Center.

Ghobakhloo, M. (2018). The future of manufacturing industry: A strategic roadmap toward Industry 4.0. *Journal of Manufacturing Technology Management*, *29*(6), 910–936. doi:10.1108/JMTM-02-2018-0057

Ghode, D. J., Yadav, V., Jain, R., & Soni, G. (2020). Blockchain adoption in the supply chain: An appraisal on challenges. *Journal of Manufacturing Technology Management*, *32*(1), 42–62. doi:10.1108/JMTM-11-2019-0395

Gunasekera, D., & Valenzuela, E. (2020). Adoption of blockchain technology in the Australian grains trade: An assessment of potential economic effects. *Economic Papers*, *39*(2), 152–161. doi:10.1111/1759-3441.12274

Han, J., Huang, Y., Kumar, K., & Bhattacharya, S. (2018). Time-varying dynamic topic model: A better tool for mining microblogs at a global level. *Journal of Global Information Management*, *26*(1), 104–119. doi:10.4018/JGIM.2018010106

Hancer, E. (2020). New filter approaches for feature selection using differential evolution and fuzzy rough set theory. *Neural Computing & Applications*, *32*(7), 2929–2944. doi:10.1007/s00521-020-04744-7

Hortovanyi, L., Szabo, R. Z., & Fuzes, P. (2021). Extension of the strategic renewal journey framework: The changing role of middle management. *Technology in Society*, *65*, 101540. doi:10.1016/j.techsoc.2021.101540

Hsieh, S. F., & Brennan, G. (2022). Issues, risks, and challenges for auditing crypto asset transactions. *International Journal of Accounting Information Systems*, *46*, 100569. doi:10.1016/j.accinf.2022.100569

Hsu, M. F., Hsin, Y. S., & Shiue, F. J. (2022). Business analytics for corporate risk management and performance improvement. *Annals of Operations Research*, *315*(2), 629–669. doi:10.1007/s10479-021-04259-x

Hsu, M. F., & Lin, S. J. (2021). A BSC-based network DEA model equipped with computational linguistics for performance assessment and improvement. *International Journal of Machine Learning and Cybernetics*, *12*(9), 2479–2497. doi:10.1007/s13042-021-01331-7

Hu, K. H., Chen, F. S., Hsu, M. F., & Tzeng, G. H. (2021). Construction of an AI-driven risk management framework for financial service firms using the MRDM Approach. *International Journal of Information Technology & Decision Making*, *20*(3), 1037–1069. doi:10.1142/S0219622021500279

Hu, Q. H., Yu, D. R., Pedrycz, W., & Chen, D. G. (2011). Kernelized fuzzy rough sets and their applications. *IEEE Transactions on Knowledge and Data Engineering*, *23*(11), 1649–1667. doi:10.1109/TKDE.2010.260

Hughes, L., Dwivedi, Y. K., Misra, S. K., Rana, N. P., Raghavan, V., & Akella, V. (2019). Blockchain research, practice and policy: Applications, benefits, limitations, emerging research themes and research agenda. *International Journal of Information Management*, *49*, 114–129. doi:10.1016/j.ijinfomgt.2019.02.005

Ilbiz, E., & Durst, S. (2019). The appropriation of blockchain for small and medium-sized enterprises. *Journal of Innovation Management*, *7*(1), 26–45. doi:10.24840/2183-0606_007.001_0004

Jeng, D. F. J., & Tzeng, G. H. (2012). Social influence on the use of clinical decision support systems: Revisiting the unified theory of acceptance and use of technology by the fuzzy DEMATEL technique. *Computers & Industrial Engineering*, *62*(3), 819–828. doi:10.1016/j.cie.2011.12.016

Jensen, R., & Shen, Q. (2005). Fuzzy-rough data reduction with ant colony optimization. *Fuzzy Sets and Systems*, *149*(1), 5–20. doi:10.1016/j.fss.2004.07.014

Jensen, R., & Shen, Q. (2007). Fuzzy-rough sets assisted attribute selection. *IEEE Transactions on Fuzzy Systems*, *15*(1), 73–89. doi:10.1109/TFUZZ.2006.889761

Jensen, R., Tuson, A., & Shen, Q. (2014). Finding rough and fuzzy-rough set reducts with SAT. *Information Sciences*, *255*, 100–120. doi:10.1016/j.ins.2013.07.033

Jo, H. J., & Choi, W. (2019). BPRF: Blockchain-based privacy-preserving reputation framework for participatory sensing systems. *PLoS One*, *14*(12), e0225688. doi:10.1371/journal.pone.0225688 PMID:31805089

Kamilaris, A., Fonts, A., & Prenafeta-Boldύ, F. X. (2019). The rise of blockchain technology in agriculture and food supply chains. *Trends in Food Science & Technology*, *91*, 640–652. doi:10.1016/j.tifs.2019.07.034

Karthik Chandra, D., Ravi, V., & Bose, I. (2009). Failure prediction of dotcom companies using hybrid intelligent techniques. *Expert Systems with Applications*, *36*(3), 4830–4837. doi:10.1016/j.eswa.2008.05.047

Kennedy, J., & Eberhart, R. C. (1995). Particle swarm optimization. *International Conference on Neural Networks, 4*, 1942-1948.

Keskin, G. A. (2015). Using integrated fuzzy DEMATEL and fuzzy C: Means algorithm for supplier evaluation and selection. *International Journal of Production Research*, *53*(12), 3586–3602. doi:10.1080/00207543.2014.980461

Khan, K. M., Arshad, J., & Khan, M. M. (2020). Investigating performance constraints for blockchain based secure e-voting system. *Future Generation Computer Systems*, *105*, 13–26. doi:10.1016/j.future.2019.11.005

Khayer, A., Talukder, M., Bao, Y., & Hossain, M. N. (2020). Cloud computing adoption and its impact on SMEs' performance for cloud supported operations: A dual-stage analytical approach. *Technology in Society*, *60*, 101225. doi:10.1016/j.techsoc.2019.101225

Kim, S. K., Kim, U. M., & Huh, J. H. (2019). A study on improvement of blockchain application to overcome vulnerability of IoT multiplatform security. *Energies*, *12*(3), 402. doi:10.3390/en12030402

Kirkland, R., & Tapscott, D. (2016). How blockchains could change the world. *The McKinsey Quarterly*, *3*, 110–113.

Kumar, A., Liu, R., & Shan, Z. (2020). Is blockchain a silver bullet for supply chain management? Technical challenges and research opportunities. *Decision Sciences*, *51*(1), 8–37. doi:10.1111/deci.12396

Lamba, K., & Singh, S. P. (2017). Big data in operations and supply chain management: Current trends and future perspectives. *Production Planning and Control*, *28*(11-12), 877–890. doi:10.1080/09537287.2017.1336787

Lee, H. S., Tzeng, G. H., Yeih, W., Wang, Y. J., & Yang, S. C. (2013). Revised DEMATEL: Resolving the infeasibility of DEMATEL. *Applied Mathematical Modelling*, *37*(10-11), 6746–6757. doi:10.1016/j.apm.2013.01.016

Leng, J., Ruan, G., Jiang, P., Xu, K., Liu, Q., Zhou, X., & Liu, C. (2020). Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: A survey. *Renewable & Sustainable Energy Reviews*, *132*, 110112. doi:10.1016/j.rser.2020.110112

Li, C., Feng, W., Han, S., Gupta, S., & Kamble, S. (2022). Digital adaptive governance, digital transformation, and service quality in logistics enterprises. *Journal of Global Information Management*, *30*(1), 1–26. doi:10.4018/JGIM.309377

Li, S., Zhang, H., Yan, W., & Jiang, Z. (2021). A hybrid method of blockchain and case-based reasoning for remanufacturing process planning. *Journal of Intelligent Manufacturing*, *32*(5), 1389–1399. doi:10.1007/s10845-020-01618-6

Liu, H., & Motoda, H. (2007). *Computational methods of feature selection, data mining and knowledge discovery*. Chapman & Hall. doi:10.1201/9781584888796

Lohmer, J., & Lasch, R. (2020). Blockchain in operations management and manufacturing: Potential and barriers. *Computers & Industrial Engineering*, *149*, 106789. doi:10.1016/j.cie.2020.106789

Low, K. F. K., & Mik, E. (2020). Pause the blockchain legal revolution. *The International and Comparative Law Quarterly*, *69*(1), 135–175. doi:10.1017/S0020589319000502

Luthra, S., Janssen, M., Rana, N. P., Yadav, G., & Dwivedi, Y. K. (2022). Categorizing and relating implementation challenges for realizing blockchain applications in government. *Information Technology & People*. Advance online publication. doi:10.1108/ITP-08-2020-0600

Maini, T., Kumar, A., Misra, R. K., & Singh, D. (2019). Intelligent fuzzy rough set based feature selection using swarm algorithms with improved initialization. *Journal of Intelligent & Fuzzy Systems*, *37*(1), 1155–1164. doi:10.3233/JIFS-182606

Mathivathanan, D., Mathiyazhagan, K., Rana, N. P., Khorana, S., & Dwivedi, Y. K. (2021). Barriers to the adoption of blockchain technology in business supply chains: A total interpretive structural modelling (TISM) approach. *International Journal of Production Research*, *59*(11), 3338–3359. doi:10.1080/00207543.2020.1868597

Meredith, J. R., Raturi, A., Amoako-Gyampah, K., & Kaplan, B. (1989). Alternative research paradigms in operations. *Journal of Operations Management*, *8*(4), 297–326. doi:10.1016/0272-6963(89)90033-8

Michelman, P. (2017). Seeing beyond the blockchain hype. *MIT Sloan Management Review*, *58*, 17–19.

Millard, C. (2018). Blockchain and law: Incompatible codes? *Computer Law & Security Report*, *34*(4), 843–846. doi:10.1016/j.clsr.2018.06.006

Mishra, H., & Venkatesan, M. (2021). Blockchain in human resource management of organizations: An empirical assessment to gauge HR and non-HR perspective. *Journal of Organizational Change Management*, *34*(2), 525–542. doi:10.1108/JOCM-08-2020-0261

O'Dair, M., & Owen, R. (2019). Financing new creative enterprise through blockchain technology: Opportunities and policy implications. *Strategic Change*, *28*(1), 9–17. doi:10.1002/jsc.2242

Opricovic, S., & Tzeng, G. H. (2003). Defuzzification within a multicriteria decision model. *International Journal of Uncertainty, Fuzziness and Knowledge-based Systems*, *11*(5), 635–652. doi:10.1142/S0218488503002387

Pawczuk, L., Holdowsky, J., Massey, R., & Hansen, B. (2020). *Deloitte's 2020 global blockchain survey-from promise to reality*. https://www2.deloitte.com/mt/en/pages/technology/articles/2020-global-blockchain-survey.html

Pawczuk, L., Massey, R., & Holdowsky, J. (2019). *Deloitte's 2019 global blockchain survey-blockchain gets down to business*. https://www2.deloitte.com/us/en/insights/topics/understanding-blockchain-potential/global-blockchain-survey-2019.html

Pawczuk, L., Massey, R., & Schatsky, D. (2018). *Breaking blockchain open Deloitte's 2018 global blockchain survey*. https://www2.deloitte.com/content/dam/Deloitte/cz/Documents/financial-services/cz-2018-deloitte-global-blockchain-survey.pdf

Pawlak, Z. (1982). Rough sets. *International Journal of Information and Computer Science*, *11*(5), 341–356. doi:10.1007/BF01001956

Prewett, K. W., Prescot, G. L., & Phillips, K. (2020). Blockchain adoption is inevitable—Barriers and risks remain. *Journal of Corporate Accounting & Finance*, *31*(2), 21–28. doi:10.1002/jcaf.22415

Qian, Y., Liang, X., Lin, G., Guo, Q., & Liang, J. (2017). Local multigranulation decision-theoretic rough sets. *International Journal of Approximate Reasoning*, *82*, 119–137. doi:10.1016/j.ijar.2016.12.008

Radzikowska, A. M., & Kerre, E. E. (2002). A comparative study of fuzzy rough sets. *Fuzzy Sets and Systems*, *126*(2), 137–155. doi:10.1016/S0165-0114(01)00032-X

Rana, N. P., Dwivedi, Y. K., & Hughes, D. L. (2022). Analysis of challenges for blockchain adoption within the Indian public sector: An interpretive structural modelling approach. *Information Technology & People*, *35*(2), 548–576. doi:10.1108/ITP-07-2020-0460

Ren, Y. S., Ma, C. Q., Kong, X. L., Baltas, K., & Zureigat, Q. (2022). Past, present, and future of the application of machine learning in cryptocurrency research. *Research in International Business and Finance*, *63*, 101799. doi:10.1016/j.ribaf.2022.101799

Riaz, M., & Hashmi, M. R. (2020). Soft rough Pythagorean m-polar fuzzy sets and Pythagorean m-polar fuzzy soft rough sets with application to decision-making. *Computational & Applied Mathematics*, *39*(16), 16. doi:10.1007/s40314-019-0989-z

Rodrigues, A. R. D., Ferreira, F. A. F., Teixeira, F. J. C. S. N., & Zopounidis, C. (2022). Artificial intelligence, digital transformation and cybersecurity in the banking sector: A multi-stakeholder cognition-driven framework. *Research in International Business and Finance*, *60*, 101616. doi:10.1016/j.ribaf.2022.101616

Rogerson, M., & Parry, G. C. (2020). Blockchain: Case studies in food supply chain visibility. *Supply Chain Management*, *25*(5), 601–614. doi:10.1108/SCM-08-2019-0300

Saberi, S., Kouhizadeh, M., & Sarkis, J. (2019a). Blockchains and the supply chain: Findings from a broad study of practitioners. *IEEE Engineering Management Review*, *47*(3), 95–103. doi:10.1109/EMR.2019.2928264

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019b). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research*, *57*(7), 2117–2135. doi:10.1080/00207543.2018.1533261

Sáez, M. (2020). Blockchain-enabled platforms: Challenges and recommendations. *International Journal of Interactive Multimedia and Artificial Intelligence*, *6*(3), 73–89. doi:10.9781/ijimai.2020.08.005

Schatsky, D. A. A., & Dongre, A. (2018). *Blockchain and the five vectors of progress*. Deloitte Insights. https://www2.deloitte.com/content/dam/insights/us/articles/4600_Blockchain-five-vectors/DI_Blockchain-five-vectors.pdf

Singla, A., Gupta, N., Aeron, P., Jain, A., Sharma, D., & Bharadwaj, S. S. (2023). Decentralized identity management using blockchain: Cube framework for secure usage of IS resources. *Journal of Global Information Management*, *31*(2), 1–24. doi:10.4018/JGIM.321755

Skowron, A., & Rauszer, C. (1992). The discernibility matrices and functions in information systems. In *Intelligent decision support* (pp. 331–362). Springer. doi:10.1007/978-94-015-7975-9_21

Swan, M. (2015). *Blockchain: Blueprint for a new economy*. O'Reilly Media.

Tandon, A., Dhir, A., Islam, A. K. M. N., & Mäntymäki, M. (2020). Blockchain in healthcare: A systematic literature review, synthesizing framework and future research agenda. *Computers in Industry*, *122*, 103290. doi:10.1016/j.compind.2020.103290

Tandon, A., Kaur, P., Mäntymäki, M., & Dhir, A. (2021). Blockchain applications in management: A bibliometric analysis and literature review. *Technological Forecasting and Social Change*, *166*, 120649. doi:10.1016/j.techfore.2021.120649

Tao, J., Sun, D., & Wu, Y. (2022). Research on information-driven trades in China. *Journal of Global Information Management*, *30*(1), 1–21. doi:10.4018/JGIM.299326

Thangavel, K., Karnan, M., & Pethalakshmi, A. (2005). Performance analysis of rough reduct algorithms in mammogram. *International Journal of Computer Vision and Image Processing*, *5*(8), 13–21.

Tian, Z., Li, M., Qiu, M., Sun, Y., & Su, S. (2019). Block-DEF: A secure digital evidence framework using blockchain. *Information Sciences*, *491*, 151–165. doi:10.1016/j.ins.2019.04.011

Tsang, E. C. C., Chen, D., Yeung, D. S., Wang, X., & Lee, J. W. T. (2008). Attributes reduction using fuzzy rough sets. *IEEE Transactions on Fuzzy Systems*, *16*(5), 1130–1141. doi:10.1109/TFUZZ.2006.889960

Tseng, C. T., & Shang, S. S. C. (2021). Exploring the sustainability of the intermediary role in blockchain. *Sustainability (Basel)*, *13*(4), 1936. doi:10.3390/su13041936

Tzeng, G. H., Chiang, C. H., & Li, C. W. (2007). Evaluating intertwined effects in e-learning programs: A novel hybrid MCDM model based on factor analysis and DEMATEL. *Expert Systems with Applications*, *32*(4), 1028–1044. doi:10.1016/j.eswa.2006.02.004

Vafadarnikjoo, A., Badri Ahmadi, H., Liou, J. J. H., Botelho, T., & Chalvatzis, K. (2021). Analyzing blockchain adoption barriers in manufacturing supply chains by the neutrosophic analytic hierarchy process. *Annals of Operations Research*. Advance online publication. doi:10.1007/s10479-021-04048-6

Vincent, N. E., Skjellum, A., & Medury, S. (2020). Blockchain architecture: A design that helps CPA firms leverage the technology. *International Journal of Accounting Information Systems*, *38*, 100466. doi:10.1016/j.accinf.2020.100466

Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98–110. doi:10.1016/j.ijpe.2016.03.014

Weill, P., & Woerner, S. L. (2018). Is your company ready for a digital future? *MIT Sloan Management Review*, *59*(2), 21–25.

Wiatt, R. G. (2019). From the mainframe to the blockchain. *Strategic Finance*, *100*(7), 26–35.

Wu, W. W. (2012). Segmenting critical factors for successful knowledge management implementation using the fuzzy DEMATEL method. *Applied Soft Computing*, *12*(1), 527–535. doi:10.1016/j.asoc.2011.08.008

Yadav, J., Misra, M., Rana, N. P., Singh, K., & Goundar, S. (2022). Netizens' behavior towards a blockchain-based esports framework: A TPB and machine learning integrated approach. *International Journal of Sports Marketing & Sponsorship*, *23*(4), 665–683. doi:10.1108/IJSMS-06-2021-0130

Yadav, V. S., Singh, A. R., Raut, R. D., & Govindarajan, U. H. (2020). Blockchain technology adoption barriers in the Indian agricultural supply chain: An integrated approach. *Resources, Conservation and Recycling*, *161*, 104877. doi:10.1016/j.resconrec.2020.104877

Zadeh, L. A. (1997). Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic. *Fuzzy Sets and Systems*, *90*(2), 111–127. doi:10.1016/S0165-0114(97)00077-8

Zhao, H. X., Xing, H. J., & Wang, X. Z. (2011). Two-stage dimensionality reduction approach based on 2DLDA and fuzzy rough sets technique. *Neurocomputing*, *74*(17), 3722–3727. doi:10.1016/j.neucom.2011.06.020

Zuo, Y. (2020). Making smart manufacturing smarter – A survey on blockchain technology in industry 4.0. *Enterprise Information Systems*, *15*(10), 1323–1353. doi:10.1080/17517575.2020.1856425

APPENDIX A

Fuzzy Rough Set Theory-Based Particle Swarm Optimization (FRST-PSO)

Fuzzy rough set theory (FRST) (Tsang et al., 2008) is commonly applied for favorable features, effectively captures the necessary information with uncertainty and vagueness (Zhao et al., 2011), and, based on Hancer (2020), is one approach for achieving a distinguished outcome in multi-objective issues. Variables related to barriers of blockchain adoption are considered as a fuzzy set with a suitable membership function for real data analysis (Jensen & Shen, 2005). In Radzikowska and Kerre (2002), the pair of fuzzy *p*-lower and *p*-upper approximations of a subset $B \subseteq \Re$ is defined in Eqs. (1) and (2), respectively:

$$\underline{R_p}B\left(x\right) = \underset{y \in \Re}{Inf}\, \eta\left(R_p\left(x,y\right), B\left(y\right)\right) \tag{1}$$

$$\overline{R_p}B\left(x\right) = \underset{y \in \Re}{Sup}\, \psi\left(R_p\left(x,y\right), B\left(y\right)\right) \tag{2}$$

for all *y* in $\Re$. Let R_p represent a fuzzy relation, and then η denotes a fuzzy implicator and ψ a triangular norm. Consequently, $\left(\underline{R}_p B\left(x\right), \overline{R}_p B\left(x\right)\right)$ is called a fuzzy rough set. According to attribute subset *F*, the authors redefine the fuzzy relation R_p as:

$$R_F\left(x,y\right) = \psi_P\left\{B_a\left(x,y\right)\right\} \tag{3}$$

Using the same measure as the rough set theory, the authors obtain the fuzzy position region $B_{pos\left(D\right)}$ (Jensen & Shen, 2007) by:

$$B_{pos\left(D\right)}\left(x\right) = \underset{P \in \Re/D}{Sup}\, B_{\underline{P}}\left(x\right) \tag{4}$$

The dependency of *D* relative to feature subset *P* is determined by:

$$\tau'_P\left(D\right) = \frac{\sum_{x \in \Re} B_{pos_p\left(D\right)}(x)}{\left|\Re\right|} \tag{5}$$

Therefore, a minimal subset (called reduct) of features arises through the hill-climbing algorithm, as in Eq. (5).

Despite FRST's adoption in academic research, determining the optimal set with this technology is still difficult. Crucial factor evaluation, which identifies the optimal set (rule) for predominant fulfillment of alternative variable selection, fills this gap. Similar models support optimization tasks in many fields, such as particle swarm optimization (PSO) (Maini et al., 2019), ant colony optimization (ACO) (Hsu & Lin, 2021), genetic algorithms (GA) (Amouzgar et al., 2021), etc.

PSO (Kennedy & Eberhart, 1995) is an ideal evolutionary algorithm for addressing multi-objective optimization (Dou et al., 2021). From the basic characteristics of evolutionary algorithms, PSO decides the best solution among potential ones (random particles) through an iteration process. The algorithm mimics animal behavior and captures the required information in complex tasks (Aydoğan et al., 2019). In PSO, there are two main factors, position c_{ih} and velocity v_{ih}, in a *K*-dimensional space. For a *K*-dimensional position, the *i*th particle at iteration t is a vector $c_i^t = \left\{c_{i1}^t, c_{i2}^t, \ldots, c_{iK}^t\right\}$, where *K* is the number of factors, and c_{ij}^t is the *j*th determinant of particle c_i^t. The velocity for the *i*th particle at iteration t is illustrated as a vector $v_i^t = \left\{v_{i1}^t, v_{i2}^t, \ldots, v_{iK}^t\right\}$.

If $\rho_i^t = \left\{\rho_{i1}^t, \rho_{i2}^t, \ldots, \rho_{iK}^t\right\}$ is the best solution, then particle i will stop searching task t, while $\rho_o^t = \left\{\rho_{o1}^t, \rho_{o2}^t, \ldots, \rho_{oK}^t\right\}$ indicates the best solution from ρ_i^t in the population at iteration t. To grasp the best solution, the velocity of each particle is modified as:

$$v_{ik}^t = v_{ik}^{t-1} + q_1 j_1 \left(L_{ik}^t - x_{ik}^t\right) + q_2 j_2 \left(L_{ok}^t - x_{ik}^t\right), k = 1, \ldots, K \tag{6}$$

where q_1 and q_2 are the acceleration constants. Here, j_1 and j_2 are random functions in the range [0, 1]. Each particle moves its current position toward a new position through Eq. (7):

$$x_{ik}^{t+1} = x_{ik}^t + v_{ik}^t \tag{7}$$

The aggregation of forecasting preciseness and rule coverage (AFPRC) of FRST is leveraged to identify the fitness function of PSO. In short, utilizing the hybrid FRST-PSO technology determines the most significant criteria.

APPENDIX B

DEMATEL

DEMATEL is a tool for analyzing a structural model involving complex cause-and-effect relationships among factors. This paper thus introduces fuzzy DEMATEL technology to address uncertainty. The main processes of conventional DEMATEL and fuzzy DEMATEL approaches are described separately below.

Conventional DEMATEL

The Geneva Research Centre of the Battelle Menoria Institute introduced conventional DEMATEL with the aim of providing a feasible solution for complex phenomenon. One outstanding advantage of it is to take into account feedback relationships among the determinants of a system when investigating contextual correlations (Chen et al., 2022). Many organizations use DEMATEL to improve their operations. DEMATEL is implemented through the following four steps (Hu et al., 2021; Tzeng et al., 2007).

Step 1: Construction of the Direct-Influence Matrix A

To evaluate relationships among factors of mutual influence, domain experts used an integer scale ranging from 0 (no satisfaction) to 4 (very high satisfaction). Professionals with experience at blockchain adoption set up the direct-influence matrix ***A*** (known as an average matrix) using a pairwise comparison, as shown in Eq. (1):

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

Step 2: Normalization of the Direct-Influence Matrix A

The normalized direct-influence matrix $M = [m_{ij}]_{n\times n}$ is measured by the normalization of the direct-influence matrix $A = [a_{ij}]_{n\times n}$ with Eqs. (2) and (3):

$$M = \gamma \cdot A \tag{2}$$

$$\gamma = \min\left\{\frac{1}{\max_{1\le i\le n}\sum_{j=1}^{n} a_{ij}}, \frac{1}{\max_{1\le j\le n}\sum_{i=1}^{n} a_{ij}}\right\} \tag{3}$$

Step 3: Computation of the Total-Relation Matrix T

The total-relation matrix $T = \left[t_{ij}\right]_{n\times n}$ is calculated as:

$$T = M + M^2 + \ldots + M^l = M\left(I - M\right), \text{ when } \lim_{l \to \infty} M^l = \left[0\right]_{n \times n} \tag{4}$$

where $M = [m_{ij}]_{n \times n}$, $0 \le m_{ij} < 1$, $0 < \sum_{i=1}^{n} m_{ij}$, and $0 < \sum_{j=1}^{n} m_{ij} \le 1$.

Step 4: Determination of INRM

The sum of rows $\left[\sum_{j=1}^{n} t_{ij}\right]_{n \times 1}$ and the sum of columns $\left[\sum_{i=1}^{n} t_{ij}\right]_{1 \times n}^{'}$ are separately represented as direct and indirect vector $d = (d_i)_{n \times 1}$ and the influence vector $s = (s_i)_{n \times 1}$, when $i = j$ is achieved. The horizontal axis vector (***d* + *s***) exhibits the importance of the total influences among elements (criteria or dimensions). The vertical axis vector (***d* - *s***) classifies elements into two groups: cause group and affected group. When the value of (***d* - *s***) is positive, the criterion/dimension *i* influences other criteria/dimensions (called cause group). If the value of (***d* - *s***) is negative, then criterion/dimension *i* is influenced by other criteria/dimensions (called affected group). Mapping the dataset of (***d*+*s***, ***d*-*s***) sets up INRM.

Fuzzy DEMATEL

The method of "linguistic terms" is an effective form of estimation when ambiguities are involved in the decision-making task (Jeng & Tzeng, 2012). Linguistic terms can be pictured by fuzzy numbers, and triangular fuzzy numbers are the most regularly used (Wu, 2012). The fuzzy aggregation model can help achieve a favorable solution of group decision-making. A defuzzification method is required to transform fuzzy data into crisp scores when making decision judgments that involve linguistic variables, which forms the fuzzy aggregation process (Keskin, 2015). Opricovic and Tzeng (2003) leveraged CFCS to identify left (l) and right (r) scores by fuzzy minimization and fuzzy maximization functions, respectively. The total score is from a weighted average calculation. To capture the obscurity of human evaluations, a fuzzy linguistic scale with five linguistic variables {no influence, low influence, medium influence, high influence, extreme influence} is illustrated by triangular fuzzy numbers $\left(l_{ij}, m_{ij,} r_{ij}\right)$, as shown in Table 10. The fuzzy direct-influence matrix $\tilde{A}$ is calculated below based on the linguistic measures originating from domain experts:

$$\tilde{A} = [\tilde{a}_{ij}]_{n \times n}, \text{ where } \tilde{a}_{ij} = \left(a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{r}\right) \tag{5}$$

Table 10. Linguistic scale and the corresponding fuzzy numbers

Linguistic Variable	Triangular Fuzzy Numbers
No influence	(0.0, 0.1, 0.3)
Low influence	(0.1, 0.3, 0.5)
Medium influence	(0.3, 0.5, 0.7)
High influence	(0.5, 0.7, 0.9)
Extreme influence	(0.7, 0.9, 1.0)

The normalized fuzzy direct influence matrix $\tilde{M}$ can be derived through the following formula:

$$\tilde{M} = \tilde{A} / \nu, \text{ where } \nu = \max_{i,j}\left\{\max_{i} \sum_{j=1}^{n} a_{ij}, \max_{j} \sum_{j=1}^{n} a_{ij}\right\}, \; i,j \in \{1,2\ldots,n\}$$

$$\tilde{M} = [\tilde{e}_{ij}]_{n\times n}, \; \tilde{e}_{ij} = \left(e_{ij}^{l}, e_{ij}^{m}, e_{ij}^{r}\right) \tag{6}$$

$\tilde{M} = \left(M^{l}, M^{m}, M^{r}\right)$ is measured, whereby $M^{l} = \left[e_{ij}^{l}\right]_{n\times n}$, $M^{m} = \left[e_{ij}^{m}\right]_{n\times n}$, and $M^{r} = [e_{ij}^{r}]_{n\times n}$. The fuzzy total influence matrix ($\tilde{T}$) is calculated by:

$$\tilde{T} = [\tilde{t}_{ij}]_{n\times n}, \text{where } \tilde{t}_{ij} = (t_{ij}^{l}, t_{ij}^{m}, t_{ij}^{r}) \tag{7}$$

where:

$$T^{l} = [t_{ij}^{l}]_{n\times n} = M^{l}(I - M^{l})^{-1}, T^{m} = [t_{ij}^{m}]_{n\times n} = M^{m}(I - M^{m})^{-1}, and$$
$$T^{r} = [t_{ij}^{r}]_{n\times n} = M^{r}(I - M^{r})^{-1}$$

respectively. Finally, the total influence matrix $T = [t_{ij}]_{n\times n}$ is derived by the defuzzification method for the total fuzzy influence matrix $\tilde{T} = [\tilde{t}_{ij}]_{n\times n}$ such as a CFCS procedure.

APPENDIX C

Questionnaire Development

Table 11. The pre-test performance questionnaire

Dimension	Criteria	Considering the Important Evaluation of the Standard, Enter 0-10 Very Unimportant 0,1,2,…,8,9,10 Very Important
(*A*) System integration	API (application programming interface) gateway	
	Data security	
	Data share and exchange	
	Data integration	
	High cost	
(*B*) Function and reliability	Technology is unproven	
	Scalability	
	Blockchain consortium	
	Sensitivity of competitive information	
(*C*) Blockchain development talent	Blockchain-based skills and competencies	
	Employee blockchain knowledge	
	Recruitment of qualified technical personnel	
	Executives' cognition	
(*D*) Regulatory environment	Intellectual property	
	Jurisdictions	
	Data privacy	
	Enforceability of contracts	
	Current regulation	

The Official Questionnaire

An Innovative Hybrid Decision Framework for Assessing and Improving the Barriers of Blockchain Technology Adoption

Good day! This is an academic research about "An innovative hybrid decision framework for assessing and improving the barriers of blockchain technology adoption". The purpose is to improve the barriers of blockchain technology adoption.

As we are greatly impressed by your excellent accomplishment in this field, if we could have the honor of receiving your valuable opinions, the result and reliability of this study will be extremely helped. The information you provide is for academic statistical analysis only and will not be separately announced to the outside world or transferred to other applications. Therefore, please fill out the answers at ease.

Your support will be a key to the successful completion of the study. We are looking forward to the benefits if would take the time to express your opinions to be taken as reference for this study. Please accept our most sincere gratitude. Thank you very much.

Instructions for Filling Out the Questionnaire

This questionnaire is divided into four parts:

1. Instructions for completion;
2. Descriptions of dimensions and criteria;
3. Method for completion:
   a. Comparison of the impact of the four dimensions;
   b. Comparison of the impact of the 11 standards;
4. Personal data.

Table 12. Descriptions of dimensions and criteria

Dimensions/Criteria	Descriptions
(*A*) System integration	
API gateway (a_1)	Compatibility of new technology and legacy systems as well as system and data integration.
Data share and exchange (a_2)	Effective data sharing and exchange is achieved from different sources.
High cost (a_3)	The high amount of construction funds is required for blockchain introduction.
(*B*) Function and reliability	
Scalability (b_1)	The computing capabilities of blockchain technology were used in a wide range and implemented the objectives in a given time period.
Blockchain consortium (b_2)	Different blockchain consortia exists technology difference, and not all consortia can provide a feasible and integrated system.
Sensitivity of competitive information (b_3)	Protection and leakage of sensitive information on the blockchain.
(*C*) Blockchain development talent	
Blockchain-based skills and competencies (c_1)	There is sufficient supply of professionals on blockchain technology.
Recruitment of qualified technical personnel (c_2)	Whether it is possible to recruit suitable technical personnel.
Executives' cognition (c_3)	Senior executives' knowledge to blockchain.
(*D*) Regulatory environment	
Jurisdictions (d_1)	Jurisdiction issues arise from any dispute between blockchain participants.
Current regulation (d_2)	Existing national legal system related to blockchain.

Method for Completion

To complete the survey method and description, do as follows.

Respond to the level of importance and performance of each criterion, according to experts' opinions in practical experience; enter the scales specified for importance (choosing important criteria) and performance (using evaluation and improvement) by natural language.

Table 13. Comparison of the impact of the four dimensions

	A	B	C	D	E
A		4			
B					

Instructions for completing the index: No impact (0); Low impact (1); Medium impact (2); High impact (3); Very high impact (4).
Example: The impact of A on B is very high; thus, "4" is filled out at the corresponding position.

Please complete the compared levels of 11 criterions in Table 14.

Table 14. Comparison of the impact of the 11 standards

Criteria	API gateway (a_1)	Data share and exchange (a_2)	High cost (a_3)	Scalability (b_1)	Blockchain consortium (b_2)	Sensitivity of competitive information (b_3)	Blockchain-based skills and competencies (c_1)	Recruitment of qualified technical personnel (c_2)	Executives' cognition (c_3)	Jurisdictions (d_1)	Current regulation (d_2)
PI gateway (a_1)	---										
Data share and exchange (a_2)		---									
High cost (a_3)			---								
Scalability (b_1)				---							
Blockchain consortium (b_2)					---						
Sensitivity of competitive information (b_3)						---					
Blockchain-based skills and competencies (c_1)							---				
Recruitment of qualified technical personnel (c_2)								---			
Executives' cognition (c_3)									---		
Jurisdictions (d_1)										---	
Current regulation (d_2)											---

Instructions for completing the index: No impact (0); Low impact (1); Medium impact (2); High impact (3); Very high impact (4).

Fu-Hsiang Chen is a Full Professor in the Department of Accounting, at Chinese Culture University, Taipei, Taiwan. His researches covers Multiple Criteria Decision Making (MCDM), Risk Analysis and Management, and Artificial Intelligence Applications. He has been published more than 40 journal papers and international proceedings.

Kuang-Hua Hu is an Associate Professor in Accounting School, Nanfang College Guangzhou, China. His researches interests include Multiple Criteria Decision Making (MCDM), performance evaluation and economic development, etc. He has been published more than 40 journal papers and internal proceedings.

Sin-Jin Lin received her doctoral degree from Department of Business Administration at National Central University, Taiwan. She currently works as an associate professor in the Department of Intelligent Commerce, at National Kaousiung University of Science and Technology. Her reserach interests cover Financial accounting, Data/Text mining, Decision making and ERP.

Ming-Fu Hsu is currently an Assistant Professor in the Department of Business Management at the National United University. His research covers business analytics and decision making. He has been published more than 60 journal papers and international proceedings.