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An analytical approach for evaluating the impact of blockchain technology on sustainable supply chain performance

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ABSTRACT

Nowadays, distributed ledger technologies (e.g., blockchain technology) can play significant roles in improving supply chain management and sustainability. Blockchain technology can support responsible sourcing and ensure compliance with environmental standards by boosting traceability and transparency in sustainable supply chains. Nevertheless, blockchain technology has not been widely applied in this field due to the lack of familiarity of managers with its intrinsic characteristics. This study investigates the performance improvement, arising from the blockchain implementation, to address the problem of managerial conservatism and this technology adoption. Accordingly, an analytical approach is proposed to identify blockchain technology adoption enablers and analyze their impact on supply chain performance. At first, the main enablers, derived from the literature review, are explored using network theory. The existing causal relationships between enablers are extracted based on a multi-expertise team members' agreement. Then, the fuzzy inference system is employed to determine the weights of relationships between the identified enablers and supply chain performance-related targets. After modeling the extracted causal relationships using the fuzzy cognitive map model, a scenario is defined for each enabler, and its impact on improving supply chain performance is estimated by implementing the hybrid learning algorithm. Finally, the obtained outputs are used to prioritize the blockchain technology adoption enablers using the fuzzy data envelopment analysis model. The result of this study implies that the blockchain technology can have a significant impact on mineral supply chain performance by creating smart contracts and enhancing environmental sustainability, traceability, and transparency.

1. Introduction

A supply chain (SC) includes financial, information and product flows, and managing these components has a direct impact on an organization's competitive position (Chopra, 2019). Due to the globalization of production and technological advances, SCs have become more dynamic to achieve sustainable competitive advantage (Defee and Fugate, 2010). Accordingly, solutions for exchanging and sharing assets and information have evolved in modern SCs (Nandi et al., 2020). In this case, customers face various challenges to understand the real value of the products and the legality and ethics of the existing operations. Furthermore, since paper-based processes still exist in most organizations, this reduces the transparency and interoperability of members in SCs (Zhang, 2019). This obstacle is more visible in mineral supply chains (MSCs) due to the technical and managerial complexities of its stages from the beginning (i.e., mine exploration) to the end (i.e., market and consumption). With the sharp increase in demand for energy and mineral resources in recent decades, MSCs have also faced new challenges (IEA, 2021). In the meantime, climate change, severe socio-environmental constraints, and the economic burden of responding to sustainable development have seriously affected production management (Jang and Topal, 2020). On the other hand, consumers are seeking to purchase the products having the least negative impacts on the society and environment (Calvao and Gronwald, 2019; Tosarkani et al., 2020).

Ensuring MSC's integrity is a challenging issue for the mining industry and end consumers. This, in turn, can guarantee that minerals are supplied from a reliable source (IEA, 2021). Therefore, the importance of visibility and monitoring the assets across SCs has increased to avoid wasting time and capital (Yousefi et al., 2017). This also can facilitate making decisions on how to improve supply chain performance (SCP) and apply the integrated changes. Hence, the mining industry seeks to use innovative methods and digital technologies to boost the performance of its SCs (Jang and Topal, 2020). The digital technologies (e.g.,

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blockchain) may contribute to more than $425 billion for the stakeholders of the mining industry by 2025 Such technologies decrease 610 million tonnes of carbon dioxide emissions leading to the improvement of health and wellbeing (World Economic Forum, 2017). Therefore, digital technologies can play an important role in environmental and social sustainability while ensuring economic aspects (Alvarenga et al., 2019). In this regard, the adoption of blockchain technology (BT) improves the sustainability in SC networks in different industries (Gupta et al., 2021; Wamba et al., 2020).

BT can create trust and integrity in SCs and increase transparency by recording all information from the production place to the point of sale (Yadav and Singh, 2020). The distributed nature of this technology provides more monitoring and control in the system so that stakeholders can use their resources more efficiently (Leonida, 2020). BT can bring about significant financial savings for companies, in addition to supporting SC's sustainability (Kouhizadeh et al., 2021). In fact, the adoption of BT improves the continuous tracking of products contributing to the higher quality of products and lower costs of operations in SCs. In a blockchain-based mineral supply chain (BBMSC), reliable and real-time data are shared between customers and suppliers in a secure environment (Ren et al., 2020). In other words, tracking the ownership of goods (i.e., raw materials and ores), ensuring the authenticity of the raw material production, and removing counterfeit products are provided in a BBMSC (Leonida, 2020; Kotze, 2020). In a BBMSC, social and environmental issues can be handled by creating smart contracts (da Cruz et al., 2020). Such contracts ensure producing products with a lower carbon footprint within ethical and fair-paying frameworks. Thus, BT can be considered the key to tracking a set of social and environmental parameters to improve sustainability (da Cruz and Cruz, 2020; Leonida, 2020).

Despite the growing importance of BT in managing complex SCs, particularly MSCs, some organizational, technological, and environmental barriers have a deterrent effect on blockchain technology adoption (BTA). To improve this situation, recent research in this area has focused on investigating BTA barriers (Yadav et al., 2020; Kouhizadeh et al., 2021). However, it can be said that most challenges arise from the lack of special attention to the importance of BTA enablers and managerial conservatism. BTA enablers are the intrinsic characteristics of BT that increase the technology adoption rate in SCs. These characteristics are created in an SC after BT implementation and affect the SCP. If organizations know that implementing this technology facilitates SCM and has a significant impact on improving their performance, some of the existing barriers will be removed automatically. Therefore, examining BTA enablers and evaluating their impact on SCP is of great importance, especially in addressing inter-organizational challenges. Modern SCs compete with each other based on cost, time, and quality of the fulfilment of customer demand (Fish, 2011). BT, on the other hand, diverts managers' attention to increasing quality, reducing delivery time, and ensuring SC's sustainability by automating the SCM process and reducing associated costs (Tian, 2016; Alvarenga et al., 2019). Therefore, creating transparency, security, and trust in the system resulting from BT implementation can, directly and indirectly, affect the determinants of SCP.

The current study is the first to broadly investigate BTA enablers and their impact on MSC performance based on an analytical framework and multi-expertise team perspectives. This research provides theoretical and practical implications in guiding decision-makers (DMs) to adopt BT in MSCs efficiently. There are five main research questions that we address in this study as follows:

1. What are the intrinsic characteristics of BT that increase the technology adoption rate in MSCs?
2. Can BTA enablers be investigated theoretically to address managerial conservatism?
3. What are the causal relationships between BTA enablers?
4. What are the most important BTA enablers considering SCP concept?
5. Does BTA increase social and environmental sustainability?

In the current study, we introduce an analytical approach to evaluate the impact of BTA on improving MSC performance considering the sustainability concept. In this regard, the first aim of this research is to identify BTA enablers in MSCs through a comprehensive literature review and insights received from the multi-expertise team. Then, these enablers are explored using network theory (NT) and divided into two categories considering environmental context, including SC view-related enablers and external view-related enablers. This research uses NT to further explain BTA enablers for MSC management while extending theoretical underpinning to deal with the inter-organizational challenges. Then, an analytical approach is developed based on the fuzzy cognitive map (FCM) and fuzzy slack-based data envelopment analysis (FSDEA) to model the relationships between BTA enablers and prioritize them. FCM used in this approach allows DMs to model multiple factors and their causal relationships in a complex system and analyze their effects on system objectives using scenario-making techniques and learning algorithms (Bakhtavar et al., 2021). Reducing the dependence of outputs on experts' opinions using the learning algorithms is another advantage of this model (Onari et al., 2021). Notably, a fuzzy inference system (FIS) is employed in this study to aggregate the multi-expertise team's linguistic descriptions on weights of existing causal relationships between identified enablers and SCP-related targets in the FCM model. The proposed approach evaluates the impact of each of the BTA enablers on improving MSC performance based on the target nodes (i.e., cost, quality, and response time). Furthermore, the FSDEA model is developed to identify the most effective BTA enablers. The output of the proposed approach supports organizations to adopt BT in their SCs to address the sustainability-related issues and improve their overall performance.

The remainder of this study is organized as follows: Section 2 is dedicated to providing theoretical background on BT and its integration in MSC. In addition to examining the MSC and BBMSC and discussing NT, BTA enablers are extracted by reviewing recent studies about BTA in SCM. In Section 3, supplementary explanations of the FCM and FSDEA models are presented. Then, the proposed approach is described in detail in Section 4. In Section 5, the output of the proposed approach is discussed comprehensively. A conceptual comparison between the features of the current study and previous research is also provided in this section. Section 6 discusses the theoretical and managerial implications of this study. Finally, in Section 7, concluding remarks and suggestions for future research are presented.

2. Theoretical background

This section will introduce the theoretical background of this research, derived from three main literature streams. In the first subsection, BT and its types are investigated. The characteristics of a BBMSC and its active members, compared to a traditional one, are discussed in Subsection 2.2. Subsection 2.3 reviews recent research on BTA in SCs, and Subsection 2.4 discusses NT and provides a list of BTA enablers focusing on MSCs. Finally, the research gap is identified to highlight the main objectives of this study.

2.1. Blockchain technology

BT is the underlying technology for the cryptocurrency Bitcoin proposed by Nakamoto (2008) for financial applications and popularized after the 2008 financial crisis. Due to its unique characteristics compared to other business information technologies, BT can be used in different fields, such as healthcare, energy, and SCs, to address various issues (Kouhizadeh et al., 2021). Decentralization, immutability and encryption, security, transparency, and smart contracts are among the characteristics of BT (Kouhizadeh and Sarkis, 2018). BT uses a distributed digital ledger to keep records and transactions as encrypted time-stamped chains (Swan, 2015). A blockchain contains a chain of blocks, in which each block consists of a cryptographic hash of the previous block, timestamp, and multiple transactions (Nofer et al., 2017). Based on this unique data structure, once a new transaction is created in the system, a block is built with a link with the previous blocks and added to the distributed ledger. Before adding transactions, decentralized consensus based on the validation of the majority of participants is used instead of central authorities and intermediaries to ensure the credibility of transactions (Kouhizadeh and Sarkis, 2018). Based on the type of access to data, BT can be defined as public and private. Any user can interact with other network participants and record and track the transactions in a public BT because ledgers are publicly available (Ølnes et al., 2017). Due to the existence of unknown users and the lack of trust among them, public BT requires a high level of security and reliability (Zheng et al., 2017). These features have led to the development of popular cryptocurrencies, such as Bitcoin on public BT. In a private BT, ledgers are shared among the private group of authorized users and participants, and data access is also restricted to this group (Kouhizadeh and Sarkis, 2018). Accordingly, most companies select private BTs over public ones due to their unwillingness to reveal critical information (Kouhizadeh et al., 2020).

2.2. MSC-BT integration

MSCis one of the most complex SCs due to its multiplicity of members. Activities in MSCs are linear, and each member cannot access information about products, processes, and activities in progress from the beginning to the end of the chain (Calvao and Gronwald, 2019). In other words, MSC members have relationships with their direct partners, and if any of these connections are lost, SC's integration and coordination will be problematic. As indicated in Fig. 1, mining companies carry out exploration and mining activities in the first phase of an MSC (Van Den Brink et al., 2019). Then, traders purchase ore from mineral suppliers (extractors), deliver it to smelters/refiners, and after this process, the pure metal produced has been sold to semi-finished plants (Mateus and Martins, 2021; Van Den Brink et al., 2019). In addition to upgrading operations, metal ingots are formed in different molds. Then, the product of smelting and refining units is sent to the main manufacturing plants to produce the final product (Van Den Brink et al., 2019). Wholesalers and distributors are other MSC members responsible for distributing manufactured products. This stage of an SC seeks to establish a link between the manufacturer and the retailers (Mateus and Martins, 2021). Finally, consumers purchase the products from local malls and markets (i.e., retailers). Mineral recycling operations are performed by metal and mineral recovery centers due to the economic (i. e., high extraction costs of raw materials) and environmental (i.e., depletion of natural resources) considerations (Carvalho, 2017).

Nowadays, the adoption of BT has received great attention due to the need for process transparency, facilitating real-time data access, tracking products, and focusing on the concept of sustainability (Kouhizadeh et al., 2021). Some investigations have tried to apply the BT-related concepts in the mining industry, but the study of BTA enablers in MSCs remains intact. Ren et al. (2020) introduced a data-sharing mechanism using BT and its implementation steps. This mechanism ensures data quality and intellectual property protection in various mineral resources exploration compared to traditional data-sharing methods. Qiang et al. (2021) proposed a BT data security monitoring system to implement practical coal mine safety production. This monitoring system protects the safety data that are easy to be tampered with and deleted maliciously. Calvão and Archer (2021) investigated the BT-based digital extraction concept in improving the traceability of MSCs. The ambiguity of implementing BT-enabled traceability systems is one of the reasons that causes inequalities in resource use.

In recent years, the complexity of stakeholder management has been raised due to increasing the numbers of stakeholders in the organizational networks and the need for developing corporate social responsibility (Ackermann and Eden, 2011; Borgatti and Halgin, 2011). The business relationships become more transparent by applying blockchain-based solutions, which can strengthen trust between stakeholders (Yadav and Singh, 2020; Mangla et al., 2020). The integrity (i.e., one of the BTA enablers) in BBMSC leads to making the product and activity information visible in a secure environment for stakeholders (Calvao and Gronwald, 2019). In the blockchain-based SC, unlike the traditional SC, the role of three major entities, including registrars, certifiers, and standards organizations, are considered in addition to actors (Saberi et al., 2019). The actors in a BBMSC are the core members of the traditional MSC along with insurance companies, banks and financial institutions, and logistics service providers that must be certified by a certifier to maintain the trust system. As illustrated in Fig. 2, government agencies and environmental companies are considered as the registrars in a BBMSC that provide a unique identity to network actors. Actors in the mining industry must register before the start of mining operations. The certifiers in a BBMSC act as representatives of government agencies and provide various certifications, including health, safety, and security for the participation of actors in SC networks. Furthermore, assessors audit the status of mining activities in terms of technical, environmental, and safety requirements. In another part of BBMSCs, standard organizations determine the direction of MSC activities by defining standards schemes. These organizations seek to ensure fair trade and focus on social and environmental issues along with blockchain technological requirements.

In BBMSCs, any data or changes in existing data are considered as a new and tamper-proof block and added to the distributed ledger through a consensus-based algorithm (Calvao and Gronwald, 2019). In this case, each block consists of multiple transactions and a cryptographic hash of the previous block. Specific data or transactions are stored at any point in MSCs using a chain of blocks (RCS Global, 2017). Afterward, any data is stored across multiple locations and cannot be changed. However, existing data can be modified, but its transaction history always remains

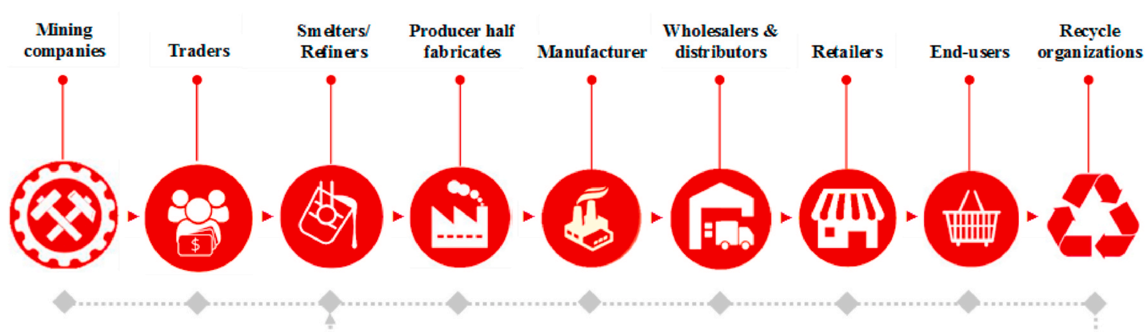

Fig. 1. A traditional mineral supply chain network.

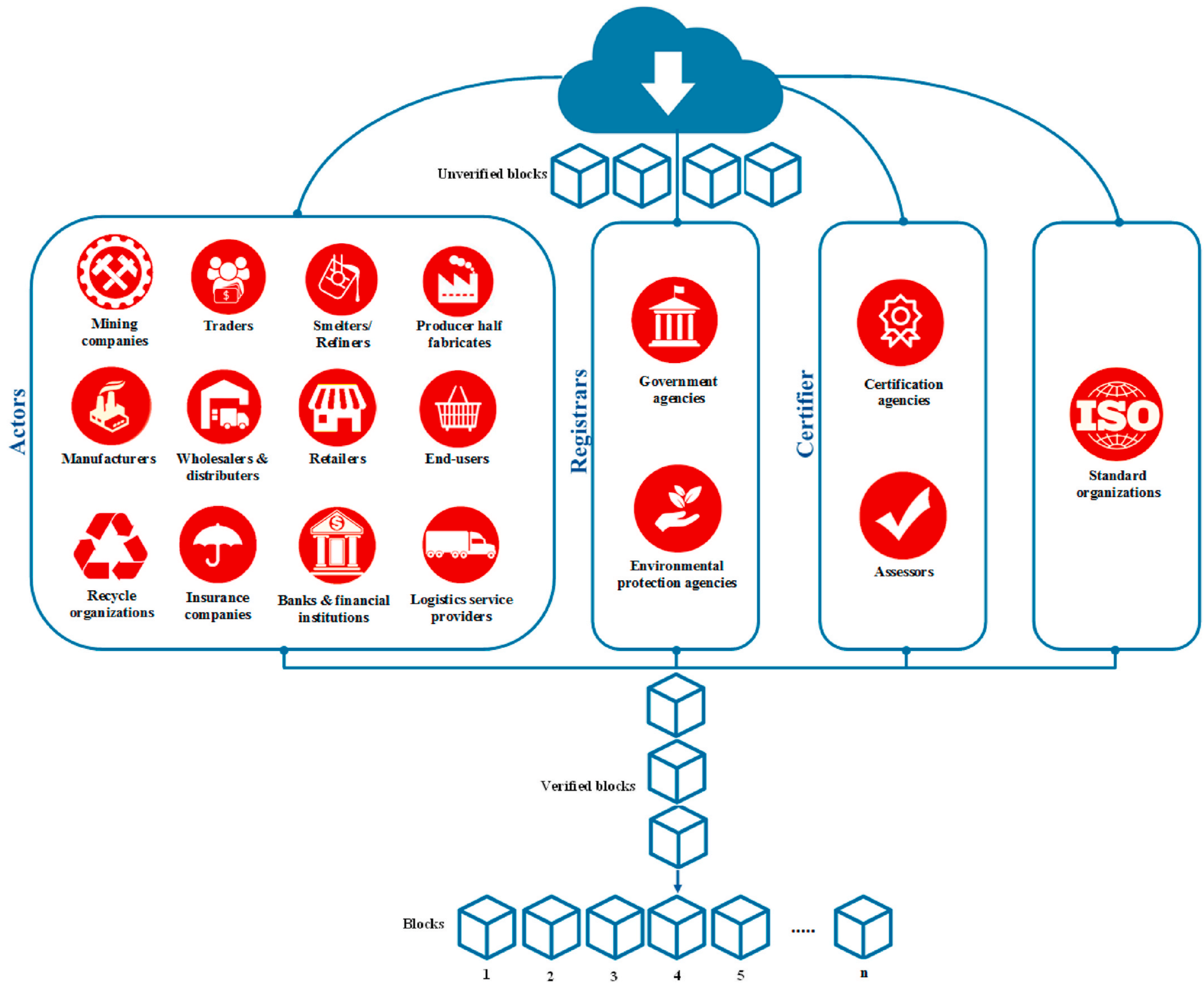

Fig. 2. A blockchain-based mining supply chain network.

in the blockchain (Weber et al., 2016). The immutability of records in BBMSCs determines the origin and increases transparency and trust in the system. BT enables the system to track the products and greenhouse gas emissions, and secure sharing of sensitive transparency information across MSCs (Hofmann et al., 2018a; World Economic Forum, 2017). As a result, this increases internal efficiency, improves sustainability, and ensures more effective communication between chain partners (Kotze, 2020). BBMSCs support local communities and stakeholders to access real-time data and information at all stages of a product life cycle.

2.3. Blockchain adoption in supply chains

In recent years, although BT has been applied in different domains, there is still some room to investigate the relationship between this technology and SCM (Wamba et al., 2020). Most recent research in this area has focused on BTA perspectives (e.g., BTA barriers) in the SCM (Kouhizadeh and Sarkis, 2018; Zhu and Kouhizadeh, 2019; Azzi et al., 2019; Kummer et al., 2020; Esmaeilian et al., 2020). BTA barriers in SCs have been categorized into four groups, including inter-organizational, intra-organizational, technical, and external barriers (Saberi et al., 2019). Some recent research has taken a step forward to analyze the challenges and enablers of BTA using statistical analysis techniques and decision-making approaches.

Queiroz and Wamba (2019) introduced an extended model based on the classical unified theory of acceptance and use of technology (UTAUT) to investigate the BTA challenges in the logistics and SCM field. This model was estimated by the partial least squares structural equation modeling (SEM) to demonstrate the existing individual behavior behind BTA. Yadav et al. (2020) applied interpretive structural modeling (ISM)-DEMATEL approach to analyze the barriers of BTA in Indian agriculture SC. Kouhizadeh et al. (2021) used the technology-organization-environment (TOE) framework and force field theory (FFT) to explore the barriers of BTA through literature review to manage sustainable SCs. Besides, this study employed the DEMATEL method to analyze the barriers identified based on academic and industry experts' opinions. To put it precisely, this study focuses mainly on the importance level of interrelationships among the identified barriers, along with the theoretical analysis of these 22 barriers.

Despite the economic and operational benefits of BT technology, companies active in SCs have little information about it due to its novelty and lack of sufficient applied studies (Longo et al., 2019). In addition to determining the existing BTA barriers, managers should pay attention to the added value and performance improvement resulting from the implementation of this technology. On the other hand, organizations require making some changes in their structures to enhance the likelihood of successful adoption (Tina Dacin et al., 2002). In this regard, DMs should investigate internal organizational adoption and technology acceptance simultaneously. Therefore, developing SC networks based on BT and identifying BTA enablers through the literature review and experts' opinions can help organizations overcome managerial and inter-organizational challenges for BTA. Nevertheless, studies focusing on this topic are nascent at present. Gupta et al. (2021) used the best-worst method (BWM) to assess and prioritize 25 key digitization enablers for improving SCP. Then, this study employed the additive value function to rank the organizations based on their performance and the important digitization enablers like tracking and localization of products. Della Valle and Oliver (2020) presented a conceptual framework based on the grounded theory (GT) to identify and investigate BT implementation enablers in SCs. This study categorized the enablers into five categories, including access, value-creation, interoperability, remote, and social enablers. Saurabh and Dey (2021) designed the survey questionnaire for identifying the potential drivers of BTA in the agri-food SC and then employed a rating-based conjoint analysis to explore the relationship between these drivers.

Pundir et al. (2020) used ISM and MICMAC techniques to assess and cluster enablers for BTA in an SC, respectively. The output of this study introduced traceability, transparency, integrity, verifiability of transactions as highly driven enablers. Yadav and Singh (2020) recognized variables affecting BTA through literature review and discussion with academic and industry experts. First, the principal component analysis (PCA) has been used to form the principal factors. Then, the causal relationships among principal factors have been analyzed using the fuzzy DEMATEL method. Kamble et al. (2020) used an integrated approach based on ISM and DEMATEL to analyze the causal relationships between enablers of BTA in agriculture SCs. The results of this study show that the most important enablers for BTA in agriculture SC are traceability, auditability, immutability and encryption, and provenance.

2.4. Network theory and blockchain adoption enablers

The application of emerging organizational theories in the adoption of BT enables DMs to expand their understanding of this technology in SCs (Treiblmaier, 2018). This, in turn, can strengthen the theoretical basis to develop conceptual models to explore BTA beyond organizational boundaries (Kummer et al., 2020). Treiblmaier (2018) investigated theories of the principal-agent, transaction cost analysis, resource-based view, and NT to illustrate the potential implications of BT for SCM using a framework built on these organizational theories. In the meantime, NT is a standard diagnostic and prescriptive tool in management consulting (Borgatti and Halgin, 2011). From the blockchain perspective, NT enables DMs to analyze the interplay within BBMSC's inter-organizational network, consisting of actors, registrars, certifiers, and standards organizations. NT focuses on mechanisms and processes that interact with network structures to investigate the nature of inter-organizational relations (IORs) and how to manage them (Treiblmaier, 2018). Considering IORs and information transparency helps DMs understand how they can manage these relations by exchanging information offered with BT (Tian, 2016). NT can elaborate on how a network structure interacts with a given process (e.g., information flow in a BBMSC) to generate outcomes for the entire network (Borgatti and Halgin, 2011).

Based on the boundary specification and focusing on environmental context, IORs in a BBMSC can be investigated from an SC view and an external view. In this regard, BTA enablers derived from a comprehensive literature review are explored from these views. After considering the SCP concept, BTA enablers can be categorized into two groups, including the SC view-related enablers (SEs) and external view-related enablers (EEs). SEs are characteristics of BT that affect SCP through empowering the actors in a BBMSC. EEs are the characteristics created in a BBMSC by involving registrars, certifiers, and standards organizations in addition to actors. Therefore, NT serves as a theoretical framework for this study to explore BTA enablers to address the managerial conservatism focusing on the environmental context. As the role of causal relationships between identified enablers can help advance this theory for BTA, this research develops an analytical approach to consider these relationships. This research derives effective BTA enablers for improving MSC performance given the proposed analytical model. In the following, a list of BTA enablers identified from the literature review focusing on the mining industry is presented in Table 1. In this table, the category assigned to each identified BTA enabler is specified by a different symbol. As BT can be used in MSCs to address social and environmental issues, three BTA enablers from the external view are considered as the representatives of three dimensions of sustainability in Table 1.

2.5. Research gap

Most existing studies have used hybrid approaches based on DEMATEL and its fuzzy version to consider interactions between either enablers or barriers. ISM and PCA are the most used methods integrated with the DEMATEL to determine the causal relationships between BTA-related factors and generate the principal component, respectively. These methods have been utilized to increase the output reliability of hybrid approaches. However, the ISM method cannot model backward relationships due to its hierarchical structure. Despite the novelty of the topic and the lack of sufficient knowledge, it is necessary to analyze factors affecting BTA in an uncertain environment. Such approaches are highly dependent on experts' opinions, and this can provide DMs with unreliable results.

The disadvantages of the DEMATEL method include the subjective and time-consuming process of setting parameters (i.e., threshold value and criteria weights) and its high dependency on unfair arguments (Li and Tzeng, 2009; Si et al., 2018). To tackle these shortcomings, data and systems analytics techniques (e.g., FCMs) can be used to model the relationships between BTA-related factors and analyze them in an uncertain environment. FCM is a powerful method to model and analyze complex and causal-based systems in various scopes, such as technology management (Son et al., 2020), manufacturing engineering (Yousefi et al., 2020), and information sciences (Chen et al., 2021). The advantages of FCM, compared to conventional multi-criteria decision-making (MCDM) methods and SEM technique, include modeling the systems with limited data, reducing the direct dependence of the output on experts' opinions, and providing more reliable results (Rezaee and Yousefi, 2018).

This study introduces an FCM-based analytical approach to model causal relationships between the BTA enablers and analyzes their impacts on improving MSC performance. The impact of these enablers on the system, focusing on social and environmental sustainability, is evaluated by considering the SCP-related targets and using the FCM learning algorithm. Furthermore, this research intends to help DMs address managerial conservatism and remove inter-organizational challenges by focusing on the most effective BTA enablers. In this regard, such enablers are identified using the FSDEA model to preserve the intelligent nature of the proposed approach. FSDEA, unlike MCDM methods, determines the weight of each criterion (i.e., SCP-related targets) by solving mathematical programming models to reduce the direct dependence of the outputs on experts' opinions. Regarding the theoretical framework, most of the previous studies have not focused on using an organizational theory to demonstrate the potential implications of BT for SCM. The current study adopts NT to explore BTA enablers and simultaneously develops an analytical approach to analyze their impacts

Table 1
The enablers of blockchain technology adoption in mineral supply chains.

Symbol	Enabler	Description	References
SE1	Auditability	BT increases auditability and efficiency by recording transaction history, guaranteeing information integrity, and making all transactions visible to all SCs entities.	Fanning and Centers (2016), Wang et al. (2019), and Yadav and Singh (2020)
SE2	Immutability and encryption	BT records any transaction or flow of data after confirmation in SCs by creating an immutable audit trail and does not allow modification, editing, and tampering to reduce susceptibility to manipulation and forgery of data.	Weber et al. (2016), Yadav and Singh (2020), and Leonida (2020)
SE3	Improved risk management	BT speeds up the final settlement of the trade process with the provision of a distributed database and reduces the risks of late payment and inefficient asset management (e.g., collateral requirements) in SCs.	Wang et al. (2019) and Kamble et al. (2020)
SE4	Reduced transaction costs	BT eliminates third-party intermediaries and decreases transaction costs and overhead costs for exchanging assets in SCs using smart contract-driven trade transactions.	Kshetri (2017), Hofmann et al. (2018b), and Yadav and Singh (2020)
SE5	Security	BT prevents manipulating the data recorded on a block in the ledger using asymmetrical cryptography and exchange validation in the form of hash and blocks and creates a secured database without losing data consistency for SCM.	Huckle et al. (2016), Kshetri (2018), and Kamble et al. (2020)
SE6	Shared database (data access control)	BT using its distributed nature allows data to be accessed by the relevant SC entities in blockchain free of human bias and error and shares the flow of information about existing processes from beginning to the end of the chain.	Ølnes et al. (2017), Wang et al. (2019), and Yadav and Singh (2020)
SE7	Transparency	BT makes data visible to stakeholders by providing an identical copy of the network at each node. In this case, all transactions are based on a consensus mechanism to increase transparency and trust in SCs.	Abeyratne and Monfared (2016), Kshetri (2017), and Kamble et al. (2020)
SE8	Flexibility	BT improves flexibility and information flow in SCM by replacing traditional processes with the self-executing smart contract and eliminating intermediaries. This helps firms prepare themselves to reconfigure the resources, strategies, and operations in collaboration with other participants in the blockchain.	Wang et al. (2020) and Zhang (2019)
SE9	Integrity	BT creates an integrated and transparent platform based on the distributed database to simplify managing the internal processes using the integration of serial numbers, bar codes, sensors, and digital tags. The internal processes include relationships with other communication service providers and suppliers.	Tian (2016), Mangla et al. (2020), and Pundir et al. (2020)
SE10	Improved inventory management	BT facilitates inventory management throughout SCs by recording any purchase order and making a copy of the information available to the stockholders using its distributed nature.	Korpelaet al. (2017) and Yadav and Singh (2020)
SE11	Customer centricity	BT makes more stream-line and automated communications at the highest trust level between SC entities and customers through providing a transparent solution.	Tian (2016) and Raju et al. (2017)
EE1	Anonymity and privacy	BT enhances information security by creating a privacy-preserving framework and cryptographic private key and ensures data anonymity for stakeholders through ring signatures.	Ouaddah et al. (2017), Ying et al. (2018), and Kamble et al. (2020)
EE2	Decentralization	BT distributes data simultaneously on different computers throughout the ledger with the provision of a decentralized database instead of storing data on a single server with the aim of enhancing trust among stakeholders.	Anjum et al. (2017), Morabito (2017), and Kamble et al. (2020)
EE3	Proving provenance	BT facilitates products tracing back to their origins and identity management by assigning a unique digital token to the product at each transaction point, and makes a trustworthy system with high data accountability.	Wang et al. (2019), Kamble et al. (2020), and Kotze (2020)
EE4	Reduced administrative procedures and settlement lead times	BT eliminates the unnecessary steps (based on paperwork) in the settlement process and the need for approval by external agencies using data attributes embedded in transactions. BT decreases administrative procedures and transactional lead times by converting estimated costs into cash payments by instantaneous transactions.	Shrier et al. (2016), Kamble et al. (2019), and Kamble et al. (2020)
EE5	Smart contracts	BT approves and supports transactions and document exchanges based on the agreed terms of stakeholders through smart contracts. These contracts improve business processes by eliminating bottlenecks and help to follow other regulations.	Xu et al. (2016), Scott et al. (2017), and Iansiti and Lakhani (2017)
EE6	Traceability	BT provides continuous traceability for the transaction of goods, data, and financial resources for stakeholders using a secure shared and decentralized database. This helps managers make decisions about the accuracy of the information and the quality of the products with high confidence. In addition to simplifying auditing, this technology can help organizations save energy and reduce carbon footprints.	Abeyratne and Monfared (2016), Tian (2016), and Yadav and Singh (2020)
EE7	Social responsibility	BT helps organizations implement efficient revenue sharing methods and produce goods in ethical and fair paying frameworks through tracking the added values, created on the way of transferring goods from the origin to the final destination. Also, the pre-determined conditions can be considered through smart contracts to raise awareness of human rights, ensure responsible sourcing, and reduce unsafe mining practices.	Hofmann et al. (2018a), Van Den Brink et al. (2019), and Alvarenga et al. (2019)
EE8	Environmental sustainability	BT can ensure the production of goods with a lower carbon footprint and reduce unsustainable mining practices, carbon emissions, and environmental costs due to non-compliance with agreed regulations by creating smart contracts.	Alvarenga et al. (2019) and World World Economic Forum (2017)
EE9	Compliance with government policy	BT helps organizations meet certain criteria and certifications based on government policy by existing processes, products, and activities in SC networks. This, in turn, simplifies the reporting process to regulatory agencies in complex SCs with a large number of members through a decentralized database.	Saberi et al. (2019) and Luthra and Mangla (2018)

on SCP. In fact, NT is used to theoretically support the analysis of enablers by the FCM-based analytical approach. This theory can also explain the nature and behavior of BTA enablers that organizational entities may consider to improve MSC performance when they adopt BT.

3. Methodology

In this section, the FCM and FSDEA models are introduced to develop an analytical approach. The purpose of this approach is to identify BTA enablers and model the relationships between them to determine the most effective ones in improving MSC performance. In the first phase, enablers affecting the adoption of this technology in MSC are identified by focusing on the sustainability concept through literature review. In the second phase, the relationships between the BTA enablers are extracted and modeled using the opinions of multi-expertise team members (TMs) and an FIS-based FCM approach, respectively. In this phase, the managerial goals associated with the SCP concept are considered in the modeling process to investigate the role of BTA in improving MSC performance. The impact of each BTA enabler on SCP-related targets is evaluated by implementing the hybrid FCM learning algorithm in the third phase. In the final phase, an FSDEA model is developed to analyze the outputs and determine the score for each BTA enabler. Accordingly, the identified BTA enablers are prioritized based on their impact on improving MSC performance. The flowchart of the implementation phases of the proposed approach is provided in Fig. 3. In the following, Subsection 3.1 discusses the FCM methodology and its hybrid learning algorithm. Then, further explanations about the FSDEA model are provided in Subsection 3.2.

3.1. Fuzzy cognitive map

The FCM model has been proposed as an AI-based system analysis model to solve complex decision-making problems based on dynamic systems. Kosko (1986) introduced the FCM by attributing real numbers (i.e., in the range [−1,1] or [0,1]) to causal relationships between concepts. This increases the efficiency of cognitive maps based on the combination of fuzzy logic, introduced by Zadeh (1965), and neural networks. In recent years, FCM has been developed increasingly by changing its basic concepts and using artificial intelligence (AI) and learning algorithms to improve its performance (Froelich and Salmeron, 2017). In other words, FCM is a supervised learning fuzzy-neural system from an AI point of view, inheriting the advantages of neural networks and fuzzy logic (Yang and Liu, 2019). Based on the advantages of FCM, this approach has been widely used to address decision-making, modeling, systems analysis, prediction, and classification problems (Bakhtavar et al., 2021). Some advantages of FCM compared to existing methods (e.g., dynamic systems, SEM, and MCDM) can be expressed as follows:

– Requiring less experimental data, the less likelihood of dealing with unreliable data and variables in comparison with dynamic systems modeling;
– Offering better performance in the convergence of solutions, and parameters' estimation in the absence of sufficient data compared to SEM;
– Modeling complex systems consisting of loop and recurrent relationships compared to SEM;
– Considering unlimited and different variables with causal relationships and reducing the dependence of outputs on experts' opinions;

Therefore, the proposed approach of this study is developed based on a well-established AI technique, namely FCM. The FCM and its learning algorithm increase the reliability in the decision-making process in the absence of sufficient data (Özesmi and Özesmi, 2004; Papageorgiou et al., 2004; Rezaee and Yousefi, 2018).

3.1.1. FCM model construction

Fig. 4 shows an example of a developed FCM model in which nodes (C_i, $i = 1, \ldots,7$) represent the concepts describing the system, and arcs (W_{ij}, $i,j = 1, \ldots,7$) represent the causal relationships between concepts. The sign on arcs (W_{ij}) indicates the type of relationship between concepts of C_i and C_j and their degree of causality or weight of their causal relationship (Rezaee and Yousefi, 2018). $W_{ij} > 0$ (positive weight) indicates a direct causal relationship, $W_{ij} < 0$ (negative weight) shows an inverse causal relationship, and $W_{ij} = 0$ illustrates the absence of a relationship between the two concepts under consideration (Onari et al., 2021). In addition, concepts indicate the information of the system, such as attributes, characteristics, qualities, variables, and states (Bakhtavar et al., 2021). These concepts can be divided into two groups based on their nature, including conventional and target concepts. In most cases, the target concepts have only input edges and are added to the FCM model to assess the system status by DMs. These targets should be defined in a way that conventional concepts in the FCM model have direct and indirect relationships with them.

After identifying concepts through literature review and expert's opinions, DMs can use semi-automatic or automatic approaches to determine the weights of causal relationships (FCM construction). In both construction approaches of the FCM model, an experienced expert identifies the causal relationships between concepts and their type. In fact, the expert's opinions are applied to confirm the existence or non-existence of these relationships. In the automatic construction approach, the FCM constructor uses historical or time-series data to determine the weight of the relationships. In this approach, these weights are calculated using the relations introduced in Schneider et al. (1998) according to their type (direct or inverse) (Bakhtavar et al., 2021). In the semi-automatic construction approach, an experienced expert directly determines the weight of each causal relationship based on their knowledge and experience instead of using historical data (Bakhtavar et al., 2019). In the semi-automatic approach, expert(s) are asked to express the weight of each relationship using numbers between [0,1] or [−1,1]. One of the advantages of the FCM model is its ability to model and analyze complex systems using limited data (Papageorgiou et al., 2004). In this regard, the semi-automatic approach enables DMs to readily model and analyze the system when they face a new issue (Rezaee and Yousefi, 2018). To put it precisely, identifying the relationships between concepts and determining the weight of these relationships can be done based on the opinions of an experienced expert or an agreement between experts. In most cases, however, the opinions of an expert are used in determining the weight of causal relationships because the final outputs of the FCM learning algorithm have low dependence on the expert's opinions. Nevertheless, when we face a new issue, it is better to cover various aspects of the problem to increase the reliability of the outputs of the FCM learning algorithm (Bakhtavar et al., 2021). In this study, we utilize an FIS to aggregate the opinions of a multi-expertise team to determine the weight of relationships.

3.1.2. FCM calculations and learning algorithm

In order to stabilize the system, mathematical formulas are applied to model relationships and exchange values of concepts. The basic formula is provided in Eq. (1); however, the mathematical calculations can vary based on the structure and type of FCM. The values of other nodes related to one node can be calculated using Eq. (1) (Groumpos and Karagiannis, 2013).

$$A_i^{(k+1)} = f\left(A_i^{(k)} + \sum_{j\neq i,j=1}^{N} A_j^{(k)}.W_{ji}\right) \tag{1}$$

where, $A_i^{(k)}$, $A_i^{(k+1)}$, and $A_j^{(k)}$ represent the value of concepts C_i in k and $k + 1$ iterations and the value of concept C_j in k iteration, respectively. $f(x)$ indicates the transformation or activation function trying to return the values obtained from the multiplication of two matrices to the specific

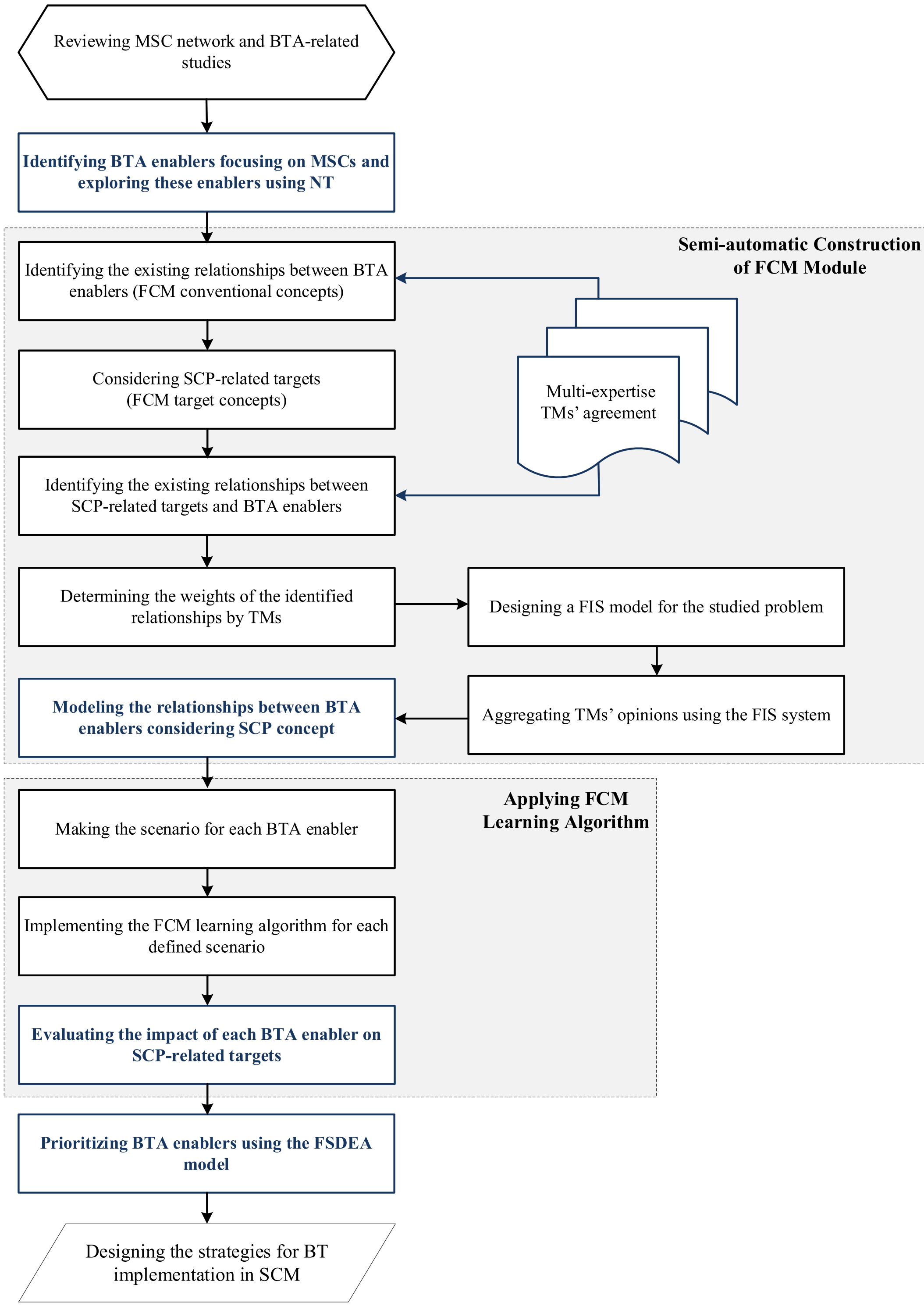

Fig. 3. The proposed research framework.

ranges (Bakhtavar et al., 2021). Several transformation functions, including hyperbolic tangent ($Tanh(\lambda x)$) and sigmoid function with different coefficients $\lambda\left(\frac{1}{1+\exp(-\lambda x)}\right)$, are employed to assign an activation level to each output (Salmeron et al., 2019; Bakhtavar et al., 2021). In this study, the sigmoid function with $\lambda = 1$ is used as an activation function to train the FCM model. The sigmoid function is differentiable and enables DMs to predict the probability that exists between the range of 0 and 1. To put it precisely, this function transfers the inputs with high values (larger than 1) to 1. Similarly, the inputs that are much smaller than 0 are snapped to 0. The shape of the sigmoid function for all possible inputs is an S-shape from 0 to 0.5 and 0.5 to 1. The FCM calculations can be continued based on Eq. (1) to reach one of the termination conditions (i.e., achieving a slight difference between learning algorithm outputs in two consecutive iterations, revealing limit cycle behavior, and indicating a chaotic behavior) (Papageorgiou et al., 2006).

In the FCM model, after identifying concepts, ascertaining the causal relationships between these concepts and their weights, scenarios are created according to the problem. Then, this model is trained using an FCM learning algorithm. Using the learning algorithms can ensure obtaining a stable and convergent FCM model based on the scenario. Furthermore, learning algorithms increase the accuracy of weight estimation and reliability in the decision-making process and reduce dependency on experts' opinions (Papageorgiou et al., 2006; Rezaee and Yousefi, 2018). This study uses a hybrid learning algorithm to train the final FCM model and calculate the impact of BTA enablers on SCP. The main aim of the hybrid learning algorithms is to incorporate the advantages of the Hebbian-based and population-based learning algorithms and address their disadvantages (Bakhtavar et al., 2021).

The non-linear Hebbian learning-differential evolution (NHL-DE) algorithm updates non-zero weights in different iterations and maintains the relationships between the concepts. In the first stage of this algorithm, the NHL algorithm is applied to calculate and update the values of weights and concepts using Eqs. (1) and (2) until meeting the termination conditions. In this study, the existence of a slight difference between the learning algorithm outputs in two consecutive iterations is considered as a termination condition. In Eq. (2), γ and η indicate the learning rates used to optimize the final solution and sgn(w_{ji}) shows the sign of weights in the FCM model. Then, the DE algorithm updates these values more accurately in the second stage based on the obtained final weight in the previous stage. After initializing the DE population in the final weight neighborhood, this algorithm is repeated for each input concept state. The weight constraint used for analyzing the causal relationships between the concepts using the hybrid learning algorithm is between 0 and 1. Generally, such weight constraints allow DMs to make qualitative comparisons between concepts.

$$w_{ji}{}^{(k)} = \gamma . w_{ji}{}^{(k-1)} + \eta\, A_i{}^{(k-1)}\left(A_j{}^{(k-1)} - sgn\left(w_{ji}{}^{(k-1)}\right) w_{ji}{}^{(k-1)} A_i{}^{(k-1)}\right) \tag{2}$$

3.2. Fuzzy data envelopment analysis

The present study applies the FSDEA to evaluate and prioritize the BTA enablers considering their impact on SCP. This model uses multiple inputs to produce multiple outputs in the fuzzy environment and assess the relative efficiencies within a group of decision-making units (DMUs) (Chen et al., 2013). This model calculates the efficiency of the kth DMU ($\widetilde{\delta}_k$) as follows:

$$\begin{aligned}
&Min\ \widetilde{\delta}_k = q - \frac{1}{m}\sum_{i=1}^{m} S_i^- / \widetilde{X}_{ik} \\
&s.t: \\
&\quad q + \frac{1}{s}\sum_{r=1}^{s} S_r^+ / \widetilde{Y}_{rk} = 1 \\
&\quad q\widetilde{X}_{ik} = \sum_{j=1}^{n} \widetilde{X}_{ij}\lambda_j^{/} + S_i^-, \quad i = 1, \dots, m \\
&\quad q\widetilde{Y}_{rk} = \sum_{j=1}^{n} \widetilde{Y}_{rj}\lambda_j^{/} - S_r^+, \quad r = 1, \dots, s \\
&\quad \sum_{j=1}^{n} \lambda_j^{/} = q \\
&\quad \lambda_j^{/} \geq 0, \quad j = 1, \dots, n \\
&\quad S_i^- \geq 0, \quad i = 1, \dots, m \\
&\quad S_r^+ \geq 0, \quad r = 1, \dots, s\ ,\ q > 0
\end{aligned} \tag{3}$$

where, $\widetilde{X}_{ij}$ and $\widetilde{Y}_{rj}$ respectively show non-deterministic inputs ($i = 1,\dots, m$) and outputs ($r = 1,\dots,s$) for each DMU_j ($j = 1,\dots,n$). In this model, $\mu_{\widetilde{X}_{ij}}$ and $\mu_{\widetilde{Y}_{rj}}$ represent the membership function of $\widetilde{X}_{ij}$ and $\widetilde{Y}_{rj}$ in the convex fuzzy set. Also, S_i^- and S_r^+ are slack variables of the FSDEA model. In Model (3), q and $\lambda_j^{/}$, respectively, indicate the variable is greater than or equal to zero and dual variables of the CCR model. Afterward, fuzzy values are converted to the crisp values using the α-cut method. In this method, both inputs $\{(X_{ij})_\alpha | 0 < \alpha \leq 1\}$ and outputs $\{(Y_{rj})_\alpha | 0 < \alpha \leq 1\}$ can be expressed as the crisp intervals of various standard α levels. Therefore, Model (3) can be transformed into the one-step programming model as follows:

$$\begin{aligned}
&Min\ (\delta_k)_\alpha^U = q - \frac{1}{m}\sum_{i=1}^{m} (S_i^-)^L \Big/ (X_{ik})_\alpha^L \\
&s.t: \\
&\quad q + \frac{1}{s}\sum_{r=1}^{s} (S_r^+)^U \Big/ (Y_{rk})_\alpha^U = 1 \\
&\quad q(X_{ik})_\alpha^L = \sum_{j=1,\neq k}^{n} (X_{ij})_\alpha^U \lambda_j^{/} + (X_{ik})_\alpha^L \lambda_j^{/} + (S_i^-)^L, \ i = 1, \dots, m \\
&\quad q(Y_{rk})_\alpha^U = \sum_{j=1,\neq k}^{n} (Y_{rj})_\alpha^L \lambda_j^{/} + (Y_{rk})_\alpha^U \lambda_j^{/} - (S_r^+)^U, \quad r = 1, \dots, s \\
&\quad \sum_{j=1}^{n} \lambda_j^{/} = q \\
&\quad \lambda_j^{/} \geq 0, \ j = 1, \dots, n, \\
&\quad (S_i^-)^L \geq 0, \ i = 1, \dots, m, \\
&\quad (S_r^+)^U \geq 0, \ r = 1, \dots, s, \ q > 0
\end{aligned} \tag{4}$$

$$\begin{aligned}
& Min\ (\delta_k)_\alpha^L = q - \frac{1}{m}\sum_{i=1}^{m}(S_i^-)^U \Big/ (X_{ik})_\alpha^U \\
& s.t: \\
& \quad q + \frac{1}{s}\sum_{r=1}^{s}(S_r^+)^L \Big/ (Y_{rk})_\alpha^L = 1 \\
& \quad q(X_{ik})_\alpha^U = \sum_{j=1,\neq k}^{n}(X_{ij})_\alpha^L \lambda_j^/ + (X_{ik})_\alpha^U \lambda_j^/ + (S_i^-)^U,\ i = 1,\dots,m \\
& \quad q(Y_{rk})_\alpha^L = \sum_{j=1,\neq k}^{n}(Y_{rj})_\alpha^U \lambda_j^/ + (Y_{rk})_\alpha^L \lambda_j^/ - (S_r^+)^L,\quad r = 1,\dots,s \\
& \quad \sum_{j=1}^{n}\lambda_j^/ = q \\
& \quad \lambda_j^/ \geq 0,\ j = 1,\dots,n, \\
& \quad (S_i^-)^L \geq 0,\ i = 1,\dots,m, \\
& \quad (S_r^+)^U \geq 0,\ r = 1,\dots,s,\ q > 0
\end{aligned} \tag{5}$$

where, $(\delta_k)_\alpha^L$ and $(\delta_k)_\alpha^U$ indicate the lower and upper bounds of the calculated efficiency for the DMU_k according to various α levels. In the above models, $(X_{ik})_\alpha^L$ and $(X_{ik})_\alpha^U$ show the lower and upper bounds of ith deterministic input for DMU_j per α level. Also, $(Y_{rk})_\alpha^L$ and $(Y_{rk})_\alpha^U$ represent the lower and upper bounds of rth non-deterministic output. Notably, the super FSDEA model, a modified version of Model (5), can be applied to increase the separability in the obtained upper bounds of efficiency (Chen et al., 2013). After calculating the lower and upper bounds of relative efficiency values for each DMU under various α levels using Models (4) and (5), DMs need a fuzzy ranking index $I(\widetilde{E}_k)$ to prioritize DMUs. As the membership function of the efficiency values is unknown, DMUs can be prioritized based on Eq. (6). In this equation, assuming that k ($k = 1,\dots,n$) and p ($p = 0,\dots,P$) as the counter number of DMUs and counter of α levels, respectively (Chen and Klein, 1997). $(E_k)_{\alpha_p}^L$ and $(E_k)_{\alpha_p}^U$ indicate the lower and upper bounds of the calculated efficiency for the DMU_k per α_p level, respectively. Based on Eq. (6), if a DMU has the highest fuzzy ranking index, it also has the highest priority.

$$I(\widetilde{E}_k) = \frac{\sum_{p=0}^{P}\left[(E_k)_{\alpha_p}^U - \min_{p,k}\left\{(E_k)_{\alpha_p}\right\}\right]}{\sum_{p=0}^{P}\left[(E_k)_{\alpha_p}^U - \min_{p,k}\left\{(E_k)_{\alpha_p}\right\}\right] - \sum_{p=0}^{P}\left[(E_k)_{\alpha_p}^L - \max_{p,k}\left\{(E_k)_{\alpha_p}\right\}\right]},\quad P \to \infty \tag{6}$$

4. Proposed approach

In this section, an analytical approach is proposed to model the causal relationships between the enablers affecting BTA and analyze their impact on SCP. The output of this approach can attract the organizations' attention to implement BT by providing a prediction of its future positive impacts. The phases of the proposed approach can be summarized as follows:

Phase I: Identifying BTA enablers focusing on MSCs and exploring these enablers using NT.

First, enablers affecting BTA in SCs are identified through a comprehensive literature review. Additionally, some enablers are added to the initial list due to the nature of MSCs and the importance of the sustainability concept based on interviews with a multi-expertise team. The final list of identified enablers is presented in Table 1. After adopting NT to explore BTA enablers, these enablers are categorized into two groups, including SEs and EEs.

Phase II: *Modeling the relationships between BTA enablers considering SCP concept.*

In this phase, causal relationships between enablers, as the concepts of the FCM, are modeled using the semi-automatic construction approach. Then, SCP-related concepts are added to the initial version of the FCM model of BTA enablers. SCP-related concepts, including "reducing costs", "increasing quality", and "reducing response time", are considered as the target nodes in the FCM model (T_l, $l = 1,2,3$). To link these targets to the initial FCM model, the relationships between target nodes and BTA enablers should also be identified based on multi-expertise TMs' agreement. After identifying the relationships between all FCM concepts, including BTA enablers and targets, the weights of these relationships are determined directly using TMs' opinions. Given the presence of three TMs with different opinions, this study aggregates their points of view using the FIS system proposed by Mamdani (1974). In this study, we design FIS systems required for all relationships between FCM concepts. The inputs and output of FIS systems are the initial weight of causal relationships determined by three TMs and their aggregated opinions, respectively.

In the initialization phases of the FIS, some linguistic variables and their corresponding membership functions are defined to express the importance of the inputs. In this study, we use these linguistic variables to enable experts to present their views in an uncertain environment instead of assigning the crisp weights to the extracted causal relationships between BTA enablers in facing a new problem. In fact, these linguistic variables are defined to determine the weight of causal relationships in the range of 0 and 1 by considering the concept of uncertainty (see Table 2). Then, a rule base (i.e., fuzzy inference engine) is designed using TMs' viewpoints. Such rules consist of antecedents (if) and consequences (then) with the aim of mapping out the given inputs to compute outputs. After this stage, non-fuzzy input variables are converted to fuzzy numbers based on the defined membership functions (Zimmermann, 2011). In the following steps, an inference is implemented on the input variables, in which fuzzy propositions are presented using the implication operator (AND), and the results are combined using the aggregation operator (OR). In the final stage, the outputs of FIS are converted to non-fuzzy values based on their membership function using defuzzification methods.

However, the current study calculates the outputs of the designed FISs using different defuzzification methods with the aim of achieving the best result in defuzzification processes. To put it precisely, a defuzzification method proposes an approximation for inference output, whereas the inference output is a fuzzy set. Three defuzzification methods, including the smallest of maximum (SOM), middle of maximum (MOM), and largest of maximum (LOM), are employed. These methods calculate the lower, middle, and upper bounds of the area of maximum values in the fuzzy output to use in the hybrid learning al-

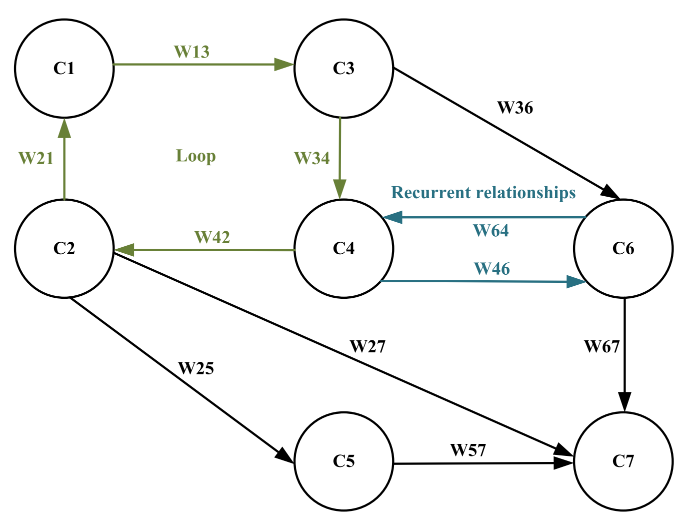

Fig. 4. A sample of an FCM.

Table 2
Linguistic variable to evaluate the power of influence of each relationship.

Linguistic variable	Membership function
Very strong (VS)	(0.75,1.00,1.00)
Strong (S)	(0.50,0.75,1.00)
Medium (M)	(0.25,0.50,0.75)
Weak (W)	(0.00,0.25,0.50)
Very weak (VW)	(0.00,0.00,0.25)

gorithm. According to the study of Zimmermann (2011), SOM, MOM, and LOM can be calculated using Eqs. (7)–(9). In Eqs. (7) and (8), $\inf_u$ and $\sup_u$ indicate upper and lower bounds, respectively. Besides, $\mu^{coceque}$ and U show the membership function of the fuzzy set u and the range of output values. Based on these equations, the weight of each relationship is obtained as a fuzzy value (SOM, MOM, LOM) by aggregating TMs' opinions. The output of this phase can be a matrix representing the weights of the identified relationships between FCM concepts in the fuzzy environment (W^0).

$$LOM = \inf_u\{u \in U : \mu^{cnceqe}(u) = \max_u\{\mu^{cnceqe}(u)\}\} \tag{7}$$

$$SOM = \sup_u\{u \in U : \mu^{cnceqe}(u) = \max_u\{\mu^{cnceqe}(u)\}\} \tag{8}$$

$$MOM = \frac{SOM + LOM}{2} \tag{9}$$

Phase III: *Evaluating the impact of each BTA enabler on SCP-related targets.*

The impact of each of the added characteristics resulting from implementing BT on SCP-related targets is evaluated in this phase. To do this, a scenario is defined for each BTA enabler and implemented using the learning algorithm. In this study, the hybrid learning algorithm is applied to decrease the dependence on experts' opinions and to examine the defined scenarios. To evaluate scenarios, it is assumed that when a scenario is implemented, the studied BTA enabler is activated (i.e., assigning the value of 1 to the representative node), and other concepts are deactivated. Then, the impact of each BTA enabler is evaluated by calculating the values of target concepts (T_l) using the hybrid learning algorithm. The output of the implementation of this algorithm for each scenario illustrates the impact of the studied BTA enabler on MSC performance in the form of system targets.

Phase IV: Prioritizing BTA enablers using FSDEA model.

After calculating the impact of each BTA enabler on SCP-related targets, these enablers are prioritized using a fixed-input FSDEA model. In this model, BTA enablers and the values obtained for targets are considered as DMUs and model outputs, respectively. The result of implementing this model in GAMS software helps identify the most effective BTA enablers. The most effective enablers are those that can significantly improve MSC performance. This results in the willingness to use this modern technology and remove managerial and inter-organizational barriers.

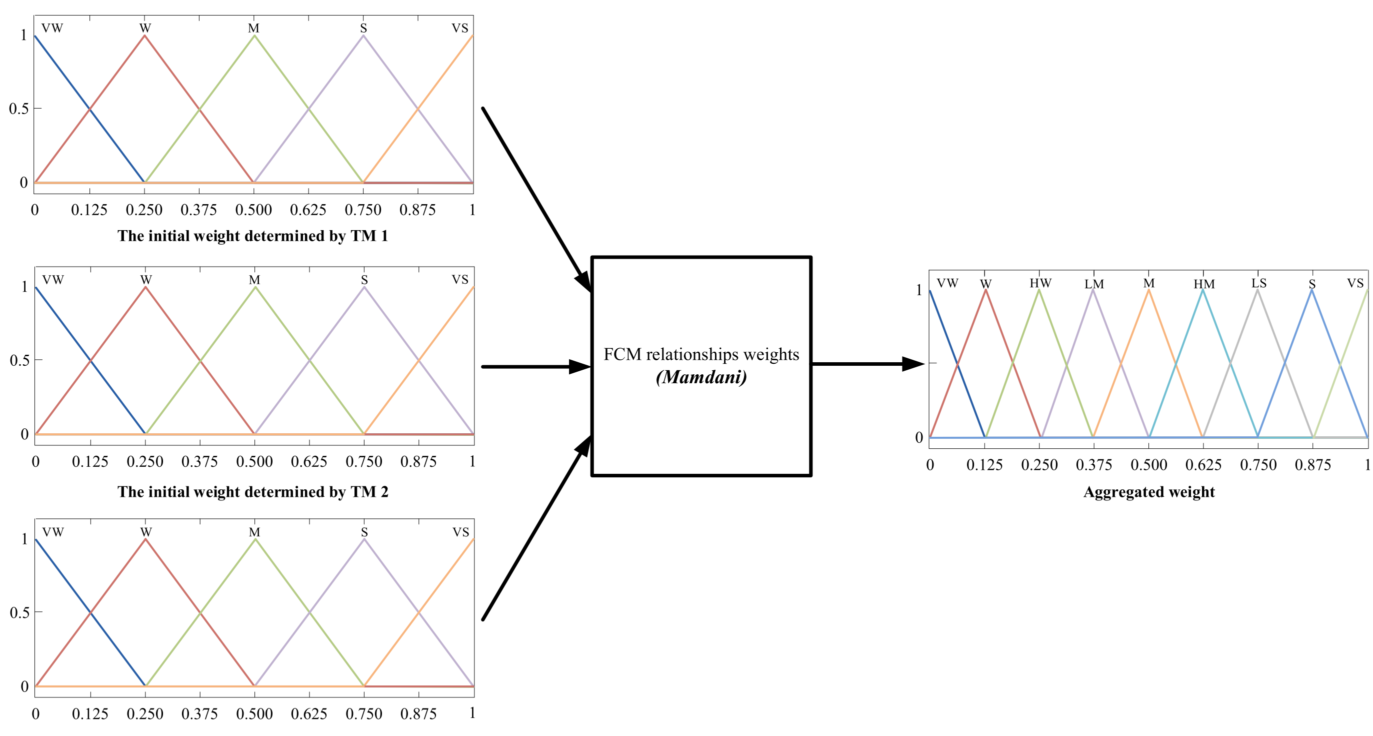

Fig. 5. Membership functions of inputs and output.

Table 3
The procedure for constructing rules.

TM 1 (*VW*)		TM 3				
		VW	W	M	S	VS
TM 2	*VW*	VW	VW	VW	W	HW
	W	VW	VW	W	HW	LM
	M	VW	W	HW	LM	M
	S	W	HW	LM	M	M
	VS	HW	LM	M	M	HM
TM 1 (*W*)		TM 3				
		VW	*W*	*M*	*S*	*VS*
TM 2	*VW*	VW	VW	W	HW	LM
	W	VW	W	HW	LM	M
	M	W	HW	LM	M	M
	S	HW	LM	M	M	HM
	VS	LM	M	M	HM	LS
TM 1 (*M*)		TM 3				
		VW	*W*	*M*	*S*	*VS*
TM 2	*VW*	VW	W	HW	LM	M
	W	W	HW	LM	M	M
	M	HW	LM	M	M	HM
	S	LM	M	M	HM	LS
	VS	M	M	HM	LS	S
TM 1 (*S*)		TM 3				
		VW	*W*	*M*	*S*	*VS*
TM 2	*VW*	W	HW	LM	M	M
	W	HW	LM	M	M	HM
	M	LM	M	M	HM	LS
	S	M	M	HM	LS	S
	VS	M	HM	LS	S	VS
TM 1 (*VS*)		TM 3				
		VW	*W*	*M*	*S*	*VS*
TM 2	*VW*	HW	LM	M	M	HM
	W	LM	M	M	HM	LS
	M	M	M	HM	LS	S
	S	M	HM	LS	S	VS
	VS	HM	LS	S	VS	VS

5. Results and discussion

In this section, the outputs of the proposed approach on investigating the BTA enablers and analyzing their impacts on SCP are discussed as follows.

5.1. Developing an FCM to model the relationships between BTA enablers

The relationships between BTA enablers are modeled using a semi-automatic FCM model. Three target nodes of "reducing costs" (T_1), "increasing quality" (T_2), and "reducing response time" (T_3) are added to the initial FCM to evaluate the impact of each enabler on SCP. As mentioned in the previous section, the weights of such relationships are determined by aggregating TMs' opinions using the FIS method. In more detail, the FIS method maps outputs from given inputs using fuzzy logic to deal with vagueness and uncertainty (Rezaee et al., 2020). In this research, we design an independent multi-inputs-single-output FIS for each identified causal relationship. Therefore, this study creates 73 FIS with similar structures (see Fig. 5) to determine the weights of all causal relationships between BTA enablers in the FCM model. The inputs of each FIS are the initial weight of a causal relationship determined by each TM (three inputs) using the linguistic variables defined in Table 2, and output is the aggregated weight.

As indicated in Fig. 5, the membership functions for three inputs are the same in each FIS. The left side of Fig. 5 consists of three inputs, and each TM can use the five linguistic variables introduced in Table 2 to determine the weight of causal relationships. Furthermore, nine linguistic variables are used to define the corresponding membership functions of output, including very weak (VW), weak (W), high weak (HW), low medium (LM), medium (M), high medium (HM), low strong (LS), strong (S), and very strong (VS). In other words, the nine membership functions shown on the right side of Fig. 5 represent the output of the FIS, which is derived from a combination of triple inputs. To put it precisely, when the different weights expressed by a multi-expertise team are combined, the range of 0 and 1 can be covered by nine membership functions. This team consists of three experienced experts (more than five years) in one of three fields investigated in this research, including SCM, mining planning, and AI. In a virtual group meeting, the existence or non-existence of causal relationships between BTA enablers is determined. Then, the initial matrix of the weights of the identified causal relationships (similar to Appendix 1) is filled by each TM using linguistic variables (see Table 2).

As mentioned, this study employs the FIS system, instead of using traditional approaches (e.g., the definitive average), to aggregate TMs' opinions. This provides an initial weighting matrix for implementing the hybrid NHL-DE algorithm. To do this, a fuzzy inference engine should be

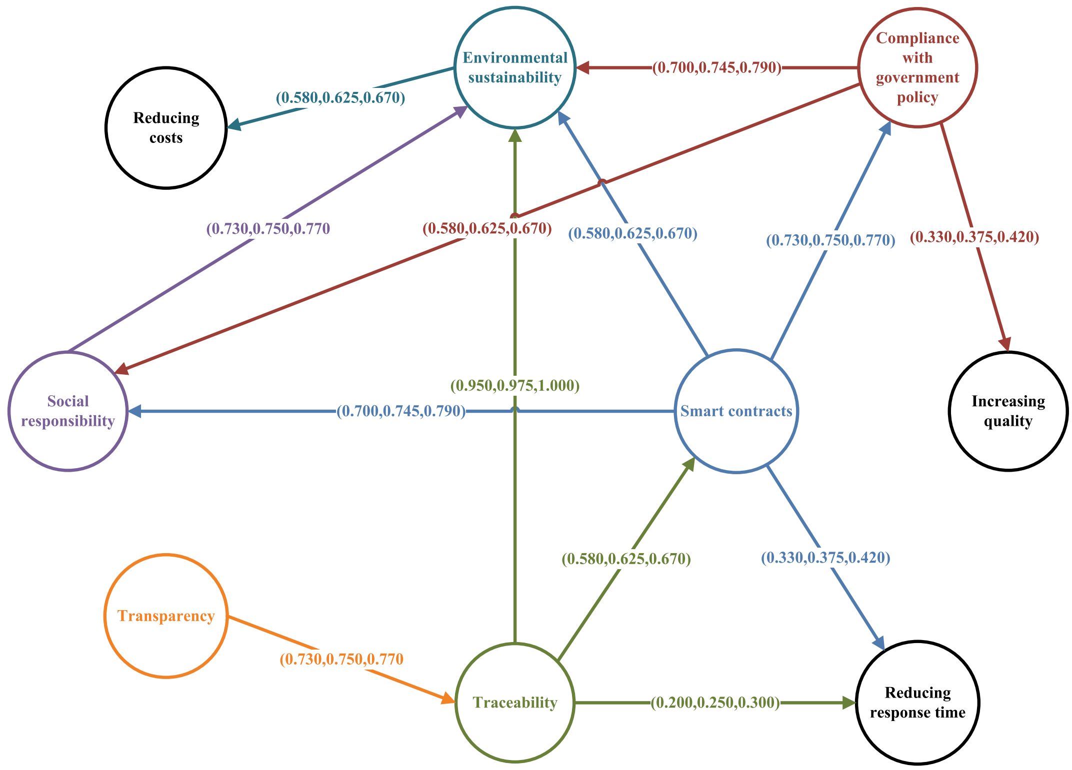

Fig. 6. A part of the FCM model of BTA enablers and SCP-related targets.

Table 4
The obtained values of SCP-related targets for each BTA enabler.

Enabler	T1		T2		T3	
	Fuzzy value	Average	Fuzzy value	Average	Fuzzy value	Average
SE1	(0.8018, 0.8133, 0.8774)	0.8308	(0.5116, 0.5142, 0.5170)	0.5143	(0.6352, 0.6497, 0.6758)	0.6536
SE2	(0.4954, 0.4910, 0.5027)	0.4964	(0.5437, 0.6497, 0.6739)	0.6224	(0.7427, 0.8177, 0.8369)	0.7991
SE3	(0.7010, 0.7135, 0.7808)	0.7318	(0.4728, 0.4975, 0.4984)	0.4896	(0.7495, 0.8214, 0.8370)	0.8026
SE4	(0.8013, 0.8289, 0.8500)	0.8267	(0.4797, 0.4962, 0.5038)	0.4932	(0.4664, 0.4817, 0.5113)	0.4865
SE5	(0.7610, 0.8207, 0.8255)	0.8024	(0.5054, 0.5413, 0.6461)	0.5643	(0.4831, 0.5530, 0.5624)	0.5328
SE6	(0.5148, 0.5178, 0.5206)	0.5177	(0.5304, 0.6186, 0.6785)	0.6092	(0.8172, 0.8270, 0.8457)	0.8300
SE7	(0.4936, 0.5308, 0.7168)	0.5804	(0.8086, 0.8252, 0.8306)	0.8215	(0.5097, 0.5793, 0.6123)	0.5671
SE8	(0.7548, 0.7679, 0.7878)	0.7702	(0.5656, 0.6069, 0.6666)	0.6130	(0.4842, 0.4896, 0.5134)	0.4957
SE9	(0.7181, 0.7506, 0.7758)	0.7482	(0.4984, 0.5037, 0.5131)	0.5051	(0.7735, 0.7852, 0.8201)	0.7929
SE10	(0.7714, 0.7879, 0.8051)	0.7881	(0.4897, 0.4990, 0.5032)	0.4973	(0.6208, 0.6630, 0.7466)	0.6768
SE11	(0.6012, 0.7142, 0.7343)	0.6832	(0.7653, 0.7732, 0.8210)	0.7865	(0.4606, 0.4899, 0.4986)	0.4830
EE1	(0.7925, 0.8496, 0.8587)	0.8336	(0.4921, 0.4991, 0.5029)	0.4980	(0.5981, 0.6143, 0.6607)	0.6244
EE2	(0.4872, 0.5031, 0.5116)	0.5006	(0.5445, 0.6542, 0.6783)	0.6257	(0.7453, 0.7841, 0.8175)	0.7823
EE3	(0.8049, 0.8165, 0.8814)	0.8343	(0.6299, 0.7089, 0.7371)	0.6920	(0.4863, 0.4978, 0.5121)	0.4987
EE4	(0.6823, 0.7873, 0.8128)	0.7608	(0.4795, 0.4876, 0.5160)	0.4944	(0.6945, 0.7012, 0.8059)	0.7339
EE5	(0.7552, 0.7884, 0.8844)	0.8093	(0.4872, 0.5022, 0.5180)	0.5025	(0.7585, 0.8165, 0.8363)	0.8038
EE6	(0.6871, 0.7856, 0.8321)	0.7683	(0.4926, 0.5083, 0.5238)	0.5082	(0.7803, 0.7991, 0.8282)	0.8025
EE7	(0.7547, 0.7954, 0.8399)	0.7967	(0.6007, 0.7109, 0.7461)	0.6859	(0.4876, 0.5048, 0.5111)	0.5012
EE8	(0.8185, 0.8469, 0.8737)	0.8464	(0.6291, 0.7431, 0.7891)	0.7204	(0.4961, 0.5113, 0.5317)	0.5130
EE9	(0.5688, 0.6514, 0.7174)	0.6459	(0.7899, 0.8148, 0.8381)	0.8143	(0.4787, 0.4924, 0.5568)	0.5093

made to compute the best output based on the different combinations of inputs. The procedure for constructing 125 rules for this inference engine has been presented in Table 3. In the determination phase of the FIS parameters, AND method, implication function, and aggregation function are set to ''min'', ''min'', and ''max'' operators, respectively. As mentioned in Section 4, this study uses three defuzzification methods (i.e., SOM, MOM, and LOM) to obtain the better output of designed FISs. In this case, each FIS is produced three values as lower, middle, and upper bounds for the weight of each identified relationship.

The FCM model is developed after calculating the weights of relationships between the concepts (i.e., the output of the FIS system). Given the existing multiple relationships and avoiding complexity, Fig. 6 shows a part of the proposed FCM consisting of nine nodes (i.e., three common BTA enablers, three sustainability concept-related BTA enablers, and three targets). Other identified relationships between the concepts of the developed FCM model are presented in Appendix 1.

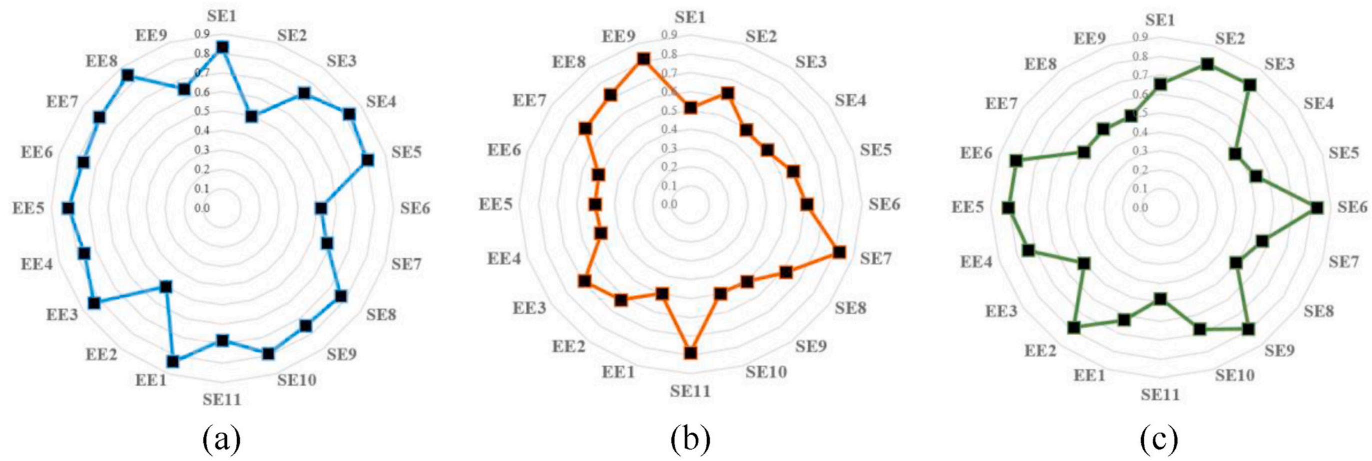

Fig. 7. The impact of BTA enablers on SCP: a) reducing costs b) increasing quality c) reducing response time.

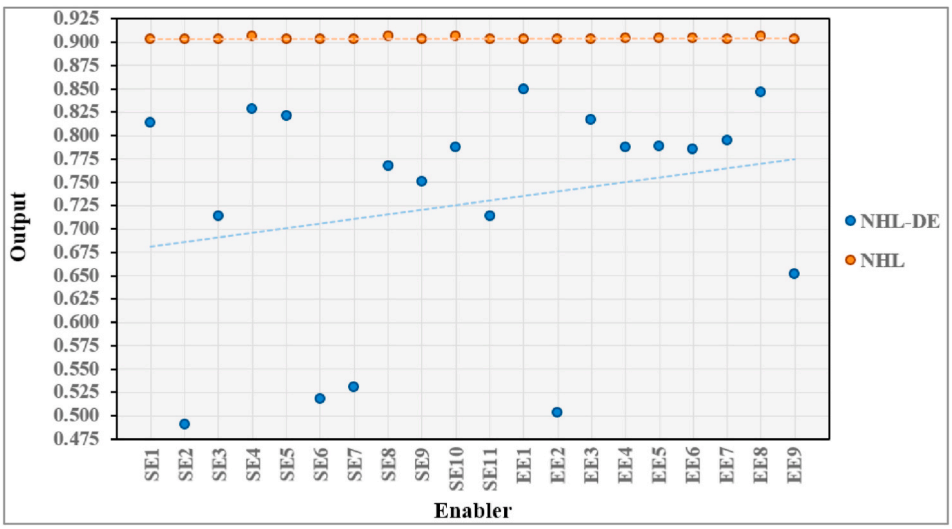

Fig. 8. Comparison of the separability of the values obtained for the first target concept.

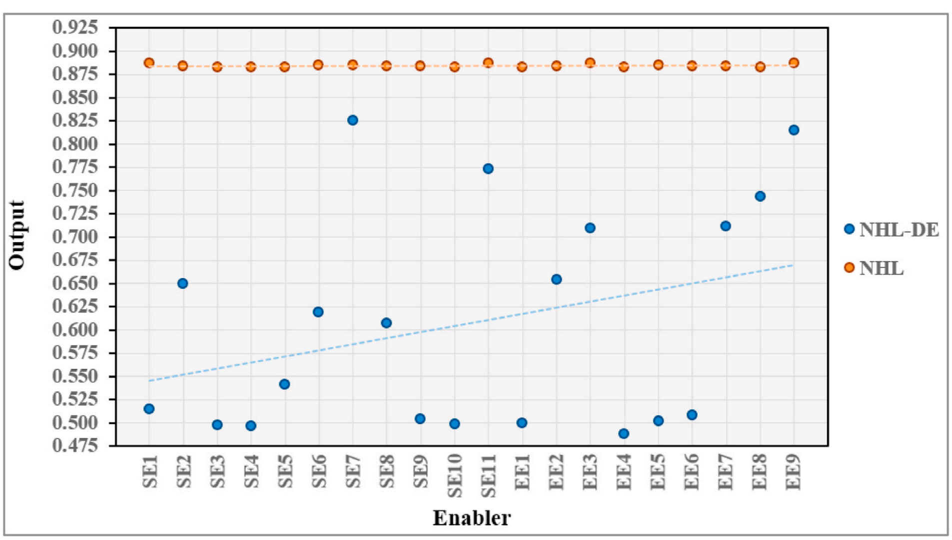

Fig. 9. Comparison of the separability of the values obtained for the second target concept.

5.2. Evaluating the impact of each BTA enabler on SCP-related targets

The impact of each enabler on the improvement of SCP is evaluated using the scenario-making technique and the hybrid learning algorithm. Accordingly, a specific scenario is defined for each BTA enabler. In each scenario, it is assumed that the BTA enabler under consideration is activated. Then, the hybrid learning algorithm is implemented according to each defined scenario, and the calculations continue until the system reaches a stable state. The output of this phase is the trained values for three target nodes. These values are considered as the impact of each BTA enabler on SCP and are presented in Table 4.

According to Table 4 and Fig. 7, BT has a significant impact on reducing the MSC's costs by enhancing environmental sustainability (EE8). In this regard, BT allows organizations to facilitate compliance with environmental standards and government policy. This happens through smart contracts and suitable platforms for continuous tracking of goods and data. In addition, the calculated average values imply that proving provenance (EE3), increasing anonymity and privacy (EE1), and improving auditability (SE1) can affect MSC's costs more than other enablers. Two enablers of increasing transparency (SE7) and compliance with government policy (EE9), along with facilitating the organization's communications with customers (SE11), have the greatest impact on the quality improvement in MSCs. In fact, BT can facilitate communication between the organizations and customers by creating a transparent solution and increasing the quality of products and services based on feedback. BT also allows members of MSCs to access data free of human bias and error so as to speed up information flow. This technology boosts the responsiveness of internal and external processes by creating shared databases (SE6) and smart contracts (EE5) and increasing traceability (EE6) in MSCs.

The validity and performance of the developed FCM model can be investigated from two perspectives. Focusing on the FCM performance in the scenario-making process, this study defines 20 scenarios to analyze the impact of each BTA enabler on target concepts (SCP-related targets). To put it precisely, we set an initial concept state by activating a BTA enabler in each scenario to describe the behavior of the proposed FCM model. Based on the network structure of this model, an efficient FCM model provides DMs with non-similar values for the target concepts in various scenarios (Felix et al., 2019). This is attributed to the different number of input and output edges for each concept under consideration.

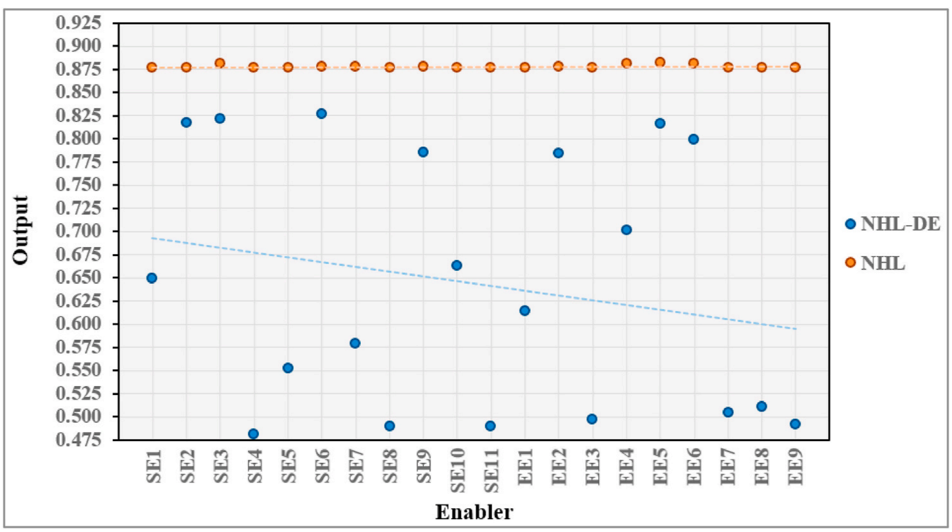

Fig. 10. Comparison of the separability of the values obtained for the third target concept.

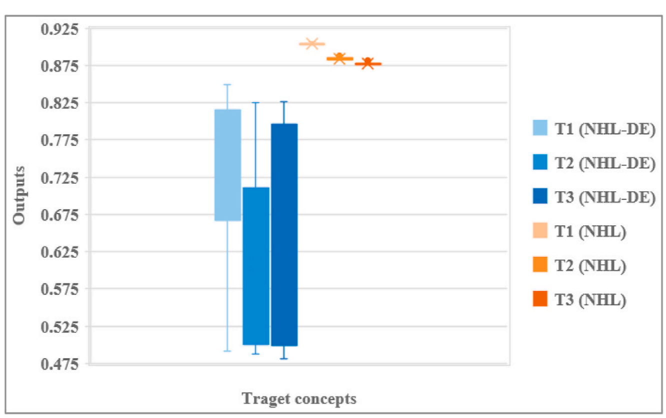

Fig. 11. The range of generated solutions for target concepts using learning algorithms.

According to Table 4, the values obtained for these targets can be distinguished after implementing 20 scenarios. This demonstrates the developed FCM model is able to consider the causal relationships between BTA enablers effectively. For example, smart contracts (EE5) affect other nine concepts, including eight BTA enablers (i.e., SE1, SE3, SE4, SE8, EE4, EE7, EE8, and EE9) and the third target (T3), directly based on the initial FCM weighting matrix (see Appendix 1). Assuming there are no other concepts in the FCM model, EE5 can affect the values of target concepts through seven of the mentioned BTA enablers except EE7 indirectly. However, EE7 also transfers the value of the concept associated with EE5 to the first and second target concepts through SE11 and EE8. In addition, EE8 is a concept with a direct output relationship with the first target node. This enabler transfers a considerable aggregated value of five concepts associated with other BTA enablers into the mentioned target concept. Based on these investigations, EE5 and EE8 can affect the SCP significantly through the determined targets due to the structure of the FCM model. Such investigations can be performed for other concepts as well, which can illustrate the performance of the proposed model in generating non-similar values for target concepts in each specific scenario.

According to the second perspective, the outputs separability refers to the range of solutions. The significant separability is acceptable for the solutions that enable DMs to have precise insight into the problem and make reliable decisions (Szwed, 2021; Onari et al., 2021). To investigate the outputs separability, this study compares the performance of two types of FCM learning algorithms, including hybrid NHL-DE and NHL algorithms. The separability of outputs associated with three target concepts are shown in Figs. 8–10. As a result, the NHL algorithm spreads outputs in a short interval without an acceptable separability. Based on Fig. 11, the generated solutions by the NHL algorithm for the first to third target concepts are in the range of [0.9030, 0.9070], [0.8829, 0.8875], and [0.8764, 0.8818], respectively. The accumulation of the generated solutions by the NHL algorithm is near the regression line (see Figs. 8–10). When DMs face such a situation, they cannot reliably distinguish the importance of BTA enablers. The lack of separability can eclipse the true value of some of the enablers in the decision-making process (Onari and Rezaee, 2020). This shortcoming is resulted from the lack of convergence of the NHL algorithm in which input vectors are independent but not orthogonal. Besides, the NHL algorithm with high probability tends to trap in the local minimum and provide similar solutions with fewer repetitions.

On the opposite side, the hybrid NHL-DE algorithm illustrates an acceptable separability among the obtained values of target concepts in various scenarios. These values, obtained from implementing the NHL-DE algorithm according to the middle bound of the initial matrix (see Appendix 1), are indicated as scatter plots in Figs. 8–10. These figures show the position of generated solutions compared to the regression line. According to Fig. 11, the generated solutions by the NHL-DE algorithm for the first to third target concepts are in the range of [0.4910, 0.8496], [0.4876, 0.8252], and [0.4817, 0.8270], respectively. These solutions are generally scattered from the regression line, which indicates the considerable separability of outputs of the proposed learning algorithm (Onari and Rezaee, 2020). As a result, the range of generated solutions approves the validity of the proposed learning algorithm. This hybrid algorithm uses DE to solve the problem of non-convergence and reinforce the NHL algorithm by keeping the information about relevant responses to increase the separability of outputs. In this case, DMs can distinguish the importance of each BTA enabler and prioritize these enablers using a mathematical programming-based model like FSDEA.

5.3. *Prioritizing BTA enablers using the FSDEA model*

The FSDEA model is developed to prioritize the BTA enablers. In this regard, BTA enablers and values of targets are considered as DMUs and evaluation criteria, respectively. The fuzzy values of targets are outputs of the FSDEA model (see Table 4), and input is a constant value equal to

Table 5
The obtained score for each BTA enabler from implementing the FSDEA model.

Enabler	Score (α = 0)		Score (α = 0.2)		Score (α = 0.4)		Score (α = 0.6)		Score (α = 0.8)		Score (α = 1)		Ranking Index	Priority
	L	U	L	U	L	U	L	U	L	U	L	U		
SE1	0.8653	1.0000	0.8788	1.0000	0.8900	1.0000	0.9015	1.0000	0.9133	1.0000	0.9255	0.9255	0.6299	10
SE2	0.7723	1.0000	0.7942	1.0000	0.8281	1.0016	0.8834	1.0050	0.9456	1.0085	1.0000	1.0115	0.6066	13
SE3	0.8521	1.0000	0.8739	1.0000	0.8954	1.0000	0.9179	1.0001	0.9414	1.0005	1.0000	1.0008	0.6732	7
SE4	0.7544	1.0000	0.7671	1.0000	0.7798	1.0000	0.7930	1.0000	0.8127	0.8542	0.8323	0.8323	0.4432	20
SE5	0.7657	1.0000	0.7899	1.0000	0.8151	1.0000	0.8407	0.9554	0.8667	0.9250	0.8968	0.8968	0.5059	18
SE6	0.8053	1.0079	0.8358	1.0057	0.8737	1.0036	0.9119	1.0036	1.0000	1.0035	1.0000	1.0035	0.6614	8
SE7	0.8093	1.0163	0.8419	1.0148	0.8813	1.0152	1.0000	1.0177	1.0000	1.0201	1.0000	1.0225	0.7043	4
SE8	0.7906	1.0000	0.8057	0.9888	0.8215	0.9531	0.8366	0.9218	0.8520	0.8934	0.8679	0.8679	0.4734	19
SE9	0.8872	1.0000	0.9026	1.0000	0.9178	1.0000	0.9336	1.0000	0.9497	0.9855	0.9664	0.9664	0.6904	5
SE10	0.8329	1.0000	0.8508	1.0000	0.8654	1.0000	0.8806	0.9594	0.8963	0.9360	0.9126	0.9126	0.5723	17
SE11	0.8149	1.0000	0.8439	1.0000	0.8699	1.0000	0.8984	1.0000	0.9294	1.0000	0.9621	0.9621	0.6206	12
EE1	0.8325	1.0000	0.8496	1.0000	0.8643	1.0000	0.8789	1.0028	0.8939	1.0059	1.0000	1.0089	0.6296	11
EE2	0.7675	1.0000	0.7902	1.0000	0.8213	1.0000	0.8698	1.0000	0.9240	1.0000	0.9752	0.9752	0.5802	16
EE3	0.8382	1.0021	0.8615	1.0000	0.8853	1.0000	0.9083	1.0000	0.9313	0.9858	0.9550	0.9550	0.6346	9
EE4	0.8256	1.0000	0.8453	1.0000	0.8648	1.0000	0.8845	1.0000	0.9042	0.9540	0.9242	0.9242	0.5878	15
EE5	0.9006	1.0235	0.9234	1.0207	0.9443	1.0179	0.9652	1.0149	0.9865	1.0117	1.0000	1.0084	0.7676	1
EE6	0.8728	1.0000	0.8961	1.0000	0.9196	1.0000	0.9435	1.0000	0.9677	1.0000	0.9924	0.9924	0.7081	3
EE7	0.8093	1.0000	0.8362	1.0000	0.8653	1.0000	0.8932	1.0000	0.9225	0.9817	0.9528	0.9528	0.6056	14
EE8	0.8491	1.0242	0.8907	1.0267	0.9334	1.0282	0.9754	1.0297	1.0000	1.0313	1.0000	1.0327	0.7501	2
EE9	0.8231	1.0031	0.8496	1.0042	0.8801	1.0053	0.9135	1.0064	1.0000	1.0075	1.0000	1.0086	0.6737	6

Table 6
Features of the present research compared to other recent studies.

Author(s)	Type of SC	Focus	Theory-driven	Data-driven	Used techniques	Uncertainty	Causal relationships	Sustainability-related factors	SCP concept	Dependence on experts' opinions	Outputs separability
Queiroz and Wamba (2019)	General SC	Drivers	UTAUT		SEM				✓	High	N/A
Yadav et al. (2020)	Agriculture SC	Barriers		✓	ISM-DEMATEL	✓	✓			High	Medium
Valle and Oliver (2020)	General SC	Enablers	GT		Conceptual framework					High	N/A
Pundir et al. (2020)	General SC	Enablers		✓	ISM-MICMAC		✓			High	Medium
Yadav and Singh (2020)	Sustainable SC	Enablers		✓	PCA-Fuzzy DEMATEL	✓	✓	✓		High	N/A
Kamble et al. (2020)	Agriculture SC	Enablers		✓	ISM-DEMATEL		✓			High	Medium
Gupta et al. (2021)	General SC	Enablers		✓	BWM-Additive value function				✓	High	High
Kouhizadeh et al. (2021)	Sustainable SC	Barriers	TOE and FFT	✓	DEMATEL		✓			High	N/A
Saurabh and Dey (2021)	Agri-food SC	Drivers		✓	Conjoint analysis		✓			Low	High
Current study	MSC	Enablers	NT	✓	FIS-FCM-FSDEA	✓	✓	✓	✓	Low	High

1 for each DMU. By solving this problem in the form of the fixed-input FSDEA model, the identified BTA enablers can be prioritized based on their impact on SCP. To do this, the fuzzy values of outputs are converted to interval values using the α-cut method. Then, the FSDEA model, consisting of Models (4) and (5), is implemented using the GAMS software based on different α cuts. Notably, the super FSDEA model is implemented for some DMUs with upper bounds of efficiency equal to 1. Hence, the calculated score for these DMUs is greater than 1. The results of implementing these models are provided in Table 5.

The fuzzy ranking index is calculated based on the obtained lower (L) and upper (U) bounds of relative efficiency values for each DMUs under various α cuts (see Eq. (6)). Based on this index, a BTA enabler with the highest score is placed in the first rank and has the greatest impact on SCP. As illustrated in Table 5, the smart contract (EE5) has the greatest impact on SCP if it is created by implementing BT. In other words, this enabler can play an important role in convincing organizations to adopt this technology. Smart contracts are one of the most effective enablers in reinforcing other inherent features of BT. EE5 gives rise to higher auditability and flexibility and reduces transaction costs and administrative procedures. Furthermore, smart contracts can simultaneously affect three sustainability related-components, including social responsibility, environmental sustainability, and compliance with government policy.

Environmental sustainability (EE8) is placed in the second rank with a score of 0.7501. This means that if BT is implemented in MSCs, environmental sustainability increases and leads to the improvement of SCP. In addition, the performance improvements arising from this enabler are accompanied by a significant reduction in MSC costs. Based on the results presented in Table 5, traceability (EE6) is ranked in the third rank with a score of 0.7081. In fact, increasing traceability allows the community, governments, customers, and the market to financially reward organizations that are acting responsibly (i.e., sustainable mining practices) in MSCs (World Economic Forum, 2017). This enabler can support the source of origin of the materials where many minerals are extracted (i.e., proving provenance). In this case, the final producers have access to all the information (e.g., the type and origin of raw materials) at different levels of MSCs and purchase the non-counterfeit raw materials from the original source. Accordingly, proving provenance can help DMs identify and prevent risks associated with conflict to increase social responsibility (Hofmann et al., 2018a). Transparency (SE7) is another effective enabler in improving MSC performance, with a score of 0.7043. Transparency enables stakeholders to access data in real-time and ensure the system operates securely through a consensus-based algorithm.

5.4. Conceptual comparison

The advantages of the proposed model compared to other recent studies are presented in Table 6. Most existing studies have tried to investigate BTA in various supply chains by developing analytical approaches. In such investigations, the concept of uncertainty has not been considered to analyze the enablers or barriers affecting BTA. This study has proposed an analytical approach in an uncertain environment to apply the sustainability and SCP concepts simultaneously.

Yadav and Singh (2020) have used an integrated approach of PCA and fuzzy DEMATEL to identify critical BTA enablers without considering the SCP-related target, including "reducing costs", "increasing quality", and "reducing response time". The present research has added these concepts to the FCM model as the target concepts. Then, we have proposed the FCM learning algorithm to evaluate the impact of each identified BTA enabler on these targets representing SCP. Accordingly, the current research, unlike the mentioned studies, has considered the

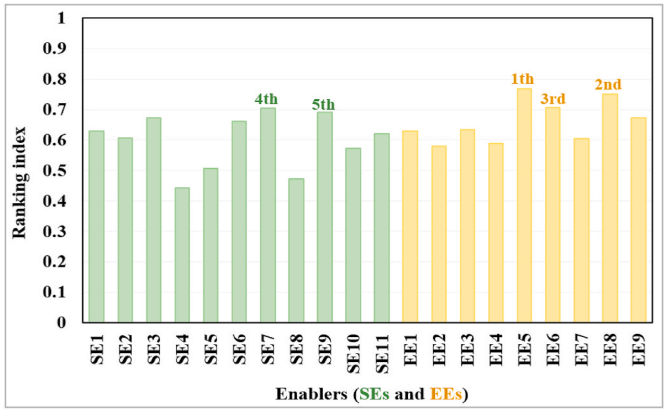

Fig. 12. The importance of BTA enablers in improving MSC performance.

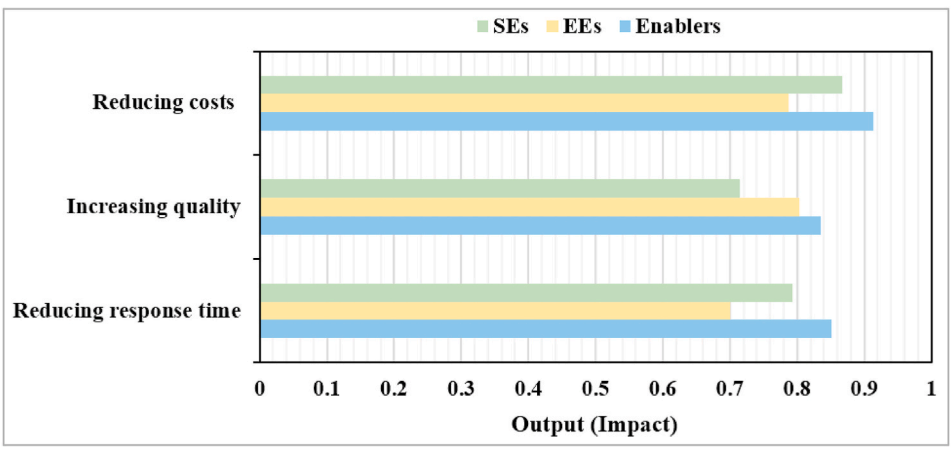

Fig. 13. The impacts of SEs and EEs on SCP-related targets.

SCP concept in the process of evaluating and prioritizing BTA enablers. Furthermore, apart from the conjoint analysis used by Saurabh and Dey (2021), the output of other approaches presented in Table 6 is highly dependent on experts' opinions. This study reduces the dependence on experts' opinions and provides more reliable outputs to DMs using the FCM learning algorithm. Also, if the output of an analytical approach has a high separability, it provides DMs with a complete prioritization of enablers or barriers. This, in turn, can enable DMs to focus on the most effective enablers or barriers in their planning. In the meantime, Queiroz and Wamba (2019) and Valle and Oliver (2020) have developed conceptual frameworks to identify the enablers, and Yadav and Singh (2020) and Kouhizadeh et al. (2021) have only sought to model the relationships between concepts. These studies have neglected to prioritize the identified enablers or barriers. In this regard, we have proposed a novel approach to identify enablers and analyze the causal relationships between them to provide a complete prioritization of BTA enablers.

6. Theoretical and managerial implications

This research further contributes to the literature by investigating the impact of BTA on MSC performance. This study provides some practical implications in guiding organizations in putting their efforts into BTA in MSCs. We also demonstrate the level of impact of the inherent features of BT considering their relationships in transforming a traditional MSC into an efficient MSC. The obtained prioritization indicates which of the identified enablers have more impact on SCP and attract the attention of organizations to adopt BT. In this regard, the outputs of this study can be employed to rebuild the inter-organizational relations among organizations active in MSCs to deal with managerial barriers. The adoption of BT in such organizations and, consequently, using smart contracts can significantly affect the SCP and sustainability of MSCs. BTA enables managers to reduce SC-related costs and response time and increase the quality of final products. To do this, managers can have a reliable tracking system by taking advantage of traceability and transparency.

This study has adopted NT to consider the environmental context in exploring BTA enablers identified from the literature review. NT focuses on assessing the importance of IORs in the BBMSC network from a relational perspective and helps DMs investigate the role of BTA enablers in the improvement of MSC performance. This study proposes an analytical approach to analyze the BTA enablers considering the SCP concept, in addition to adopting NT in exploring the identified enablers. As indicated in Table 6, this research investigates both theoretical and practical aspects of the BTA simultaneously, which have not been considered in the previous studies conducted on enablers investigation. We apply NT to support the analysis of the impact of BTA enablers (i.e., SEs and EEs) on MSC performance.

Based on the ranking score calculated for each BTA enabler, the most effective enablers are attributed to the external view category. According to Fig. 12, creating smart contracts (EE5), improving environmental sustainability (EE8), and traceability (EE6) as EEs have a significant impact on managing the BBMSC network relations, and consequently, improving MSC performance. As the attention of governments recently has shifted to the importance of sustainability in SCM, EEs play a significant role in managing MSCs. Governments pursue to increase environmental sustainability and social responsibility of various industries such as mining. Hence, the lack of attention to sustainability leads to adverse consequences for MSCs. In the meantime, the cessation of MSC activities and imposing additional costs (e.g., environmental costs) can negatively affect the MSC performance. On the other hand, increasing transparency (SE7) and integrity (SE9) can affect MSC performance greatly by creating strong relations between MSC entities. This can lead to increased trust among all entities of the BBMSC network, including actors, registrars, certifiers, and standards organizations.

As illustrated in Fig. 13, we evaluated the impacts of SEs and EEs on SCP-related targets independently to clarify the importance of each category of BTA enablers. The main aim of the identified EEs is to increase quality in MSCs, while this is the third goal of SEs. In fact, SEs have the greatest impact on reducing the costs of MSCs. This is arising from the attention of external entities (e.g., assessors and standard organizations) on improving social responsibility and environmental sustainability that can be resulted in increasing the quality of final products. To put it precisely, standard organizations determine the direction of MSC activities through defining standards schemes and help assessors ensure the quality by auditing the status of mining activities and assessing the technical conditions. On the opposite side, actors of MSC focus on the optimization of the costs and response time. Considering SEs and EEs at the same time through designing a BBMSC network can affect all SCP-related targets significantly in comparison with independent mode. Policy-makers can reduce costs and increase the quality simultaneously by the implementation of BT in MSCs. In this case, the preferences of all entities are considered in network management. This also demonstrates that the integrated implementation of BT in MSCs can help policy-makers improve IORs between all entities and overcome managerial challenges. Furthermore, sustainability-related BTA enablers can create a positive perception toward this technology in organizations and bridge the gap between SC and external entities by aligning inter-organizational processes. This, in turn, can address the initial concerns for acceptance and implementation of this emergent technology in MSCs. The outputs of this study also inform managers that they need to improve their IORs considering SC and external views to have greater and more effective BT adoption.

7. Conclusions, limitations and future research

The capabilities of BT in efficient SCM have become more pervasive in recent years. The literature review shows that various industries develop prototype concepts to assess the benefits and indicate the applications of this technology in SC networks. In the meantime, BT can reduce the irresponsibly produced minerals in MSCs and discourage SC members from using unsustainable practices. To achieve these goals, BT needs to be implemented successfully in SCs. In fact, the adoption of new technologies in SC networks is often associated with managerial and inter-organizational barriers. BT promoters should demonstrate the importance of BT implementation in MSCs to reduce the deterrent impact of these barriers. This study has introduced the intrinsic characteristics of BT (BTA enablers) and analyzed their impacts on MSC performance with the aim of addressing managerial conservatism to adopt BT. In this regard, we have adopted NT to investigate the nature of these enablers based on the environmental context to help organizations overcome managerial and inter-organizational challenges for BTA. Furthermore, we have presented an analytical approach consisting of three main phases. After identifying BTA enablers, including sustainability concept-related ones, through the literature review, FIS-based FCM and FSDEA models to analyze these enablers in the following two phases. In this regard, the FIS-based FCM model has been applied to extract the weights of causal relationships between BTA enablers and has modeled these relationships. Then, the impact of each BTA enabler on SCP-related targets has been evaluated by implementing the FCM hybrid learning algorithm. Finally, the FSDEA model has been proposed to determine the most effective BTA enablers on SCP. One of the main advantages of the proposed approach of this study was to consider SCP and sustainability concepts simultaneously in investigating BTA in the traditional MSC. The proposed methodology has increased the reliability in the decision-making process using the FCM learning algorithm and mathematical programming compared to other previous approaches. The output of this approach has implied that BT has a significant impact on improving MSC performance with a focus on creating smart contracts, increasing environmental sustainability, traceability, and transparency. Consequently, increasing traceability through proving provenance can provide all the information related to the type and origin of materials to help managers purchase non-counterfeit raw materials at different levels of an MSC. This, in turn, helps all entities in the BBMSC network mitigate risks associated with conflict to increase social responsibility.

One of the limitations of this study has been the lack of access to an experienced expert who has sufficient expertise in implementing BT in MSCs. This limitation is due to the novelty of the studied topic in this research. However, this study has tried to cover various aspects of the problem by using a three-person team with different specialties. The lack of consideration of the reliability concept in determining the weight of causal relationships can also be considered as another limitation of this research. In this regard, future researchers can apply the reliability and uncertainty concepts simultaneously to determine the weight of relationships between identified enablers using the Z-number theory. Such simultaneous considerations give rise to increase the adaptability of outputs to the real world. The application of other managerial goals-related factors in FCM modeling to reveal new dimensions of BT can be considered as another future research suggestion. To contribute to the theoretical aspects of this study, the stakeholder theory can be adopted to investigate the impact of BTA on stakeholders relations management. This provides an additional voice to stakeholders that may not be part of the decision environment.

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Appendix 1. The initial matrix of the weights of FCM relationships based on fuzzy numbers

	SE1	SE2	SE3	SE4	SE5	SE6	SE7	SE8	SE9	SE10	SE11	EE1
SE1	0	0	(0.330,0.375,0.420)	0	0	0	0	0	0	(0.450,0.495,0.540)	0	0
SE2	(0.480,0.500,0.520)	0	0	0	(0.700,0.745,0.790)	0	(0.480,0.500,0.520)	0	0	0	0	0
SE3	0	0	0	(0.450,0.495,0.540)	0	0	0	0	0	0	0	0
SE4	0	0	0	0	0	0	0	0	0	0	0	0
SE5	0	0	0	0	0	0	0	0	0	0	0	(0.730,0.750,0.770)
SE6	(0.700,0.745,0.790)	0	(0.080,0.125,0.170)	0	0	0	0	(0.730,0.750,0.770)	0	0	0	0
SE7	(0.700,0.745,0.790)	0	(0.330,0.375,0.420)	0	0	0	0	0	0	0	(0.730,0.750,0.770)	0
SE8	0	0	0	0	0	0	0	0	(0.450,0.495,0.540)	0	0	0
SE9	0	0	0	(0.480,0.500,0.520)	0	0	(0.330,0.375,0.420)	0	0	0	0	0
SE10	0	0	(0.450,0.495,0.540)	0	0	0	0	0	0	0	0	0
SE11	0	0	0	0	0	0	0	0	0	0	0	0
EE1	0	(0.200.0.250.0.300)	0	0	(0.450,0.495,0.540)	0	0	0	0	0	0	0
EE2	(0.450,0.495,0.540)	(0.450,0.495,0.540)	(0.330,0.375,0.420)	0	0	(0.950,0.975,1.000)	(0.700,0.745,0.790)	0	(0.450,0.495,0.540)	(0.580,0.625,0.670)	0	0
EE3	0	0	0	0	0	0	0	0	0	0	0	0
EE4	0	0	0	(0.580,0.625,0.670)	0	0	0	(0.700,0.745,0.790)	(0.450,0.495,0.540)	0	(0.080,0.125,0.170)	0
EE5	(0.580,0.625,0.670)	0	(0.580,0.625,0.670)	(0.700,0.745,0.790)	0	0	0	(0.330,0.375,0.420)	0	0	0	0
EE6	0	0	0	0	0	0	0	0	0	(0.730,0.750,0.770)	0	(0.450,0.495,0.540)
EE7	0	0	0	0	0	0	0	0	0	0	(0.580,0.625,0.670)	0
EE8	0	0	0	0	0	0	0	0	0	0	0	0
EE9	(0.580,0.625,0.670)	0	0	0	0	0	0	0	0	0	0	0
T1	0	0	0	0	0	0	0	0	0	0	0	0
T2	0	0	0	0	0	0	0	0	0	0	0	0
T3	0	0	0	0	0	0	0	0	0	0	0	0

	EE2	EE3	EE4	EE5	EE6	EE7	EE8	EE9	T1	T2	T3
SE1	0		0	0	0	0	0	0	0	(0.450,0.495,0.540)	0
SE2	0	(0.730,0.750,0.770)	0	0	(0.580,0.625,0.670)	0	0	0	0	0	0
SE3	0	0	0	0	0	0	0	0	0	0	(0.450,0.495,0.540)
SE4	0	0	0	0	0	0	0	0	(0.450,0.495,0.540)	0	0
SE5	0	0	0	0	0	0	0	0	0	0	0
SE6	0	(0.730,0.750,0.770)	(0.580,0.625,0.670)	0	0	0	0	0	0	0	0
SE7	0	0	0	0	(0.730,0.750,0.770)	0	0	0	0	0	0
SE8	0	0	0	0	0	0	0	(0.580,0.625,0.670)	(0.450,0.495,0.540)	0	0
SE9	0	(0.450,0.495,0.540)	(0.100,0.125,0.150)	0	(0.450,0.495,0.540)	0	0	0	0	0	0
SE10	0	0	0	0	0	0	0	0	(0.450,0.495,0.540)	0	0
SE11	0	0	0	0	0	0	0	0	0	(0.450,0.495,0.540)	0
EE1	0	0	0	0	0	0	0	0	0	0	0
EE2	0	0	(0.580,0.625,0.670)	0	0	0	0	0	0	0	0
EE3	0	0	0	0	0	(0.730,0.750,0.770)	(0.450,0.495,0.540)	0	0	(0.450,0.495,0.540)	0
EE4	0	0	0	0	0	0	0	0	0	0	(0.700,0.745,0.790)
EE5	0	0	(0.730,0.750,0.770)	0	0	(0.700,0.745,0.790)	(0.580,0.625,0.670)	(0.730,0.750,0.770)	0	0	(0.330,0.375,0.420)
EE6	0	(0.830,0.875,0.920)	0	(0.580,0.625,0.670)	0	(0.580,0.625,0.670)	(0.950,0.975,1.000)	0	0	0	(0.200,0.250,0.300)
EE7	0	0	0	0	0	0	(0.730,0.750,0.770)	0	0	0	0
EE8	0	0	0	0	0	0	0	0	(0.580,0.625,0.670)	0	0
EE9	0	0	0	0	0	(0.580,0.625,0.670)	(0.700,0.745,0.790)	0	0	(0.330,0.375,0.420)	0
T1	0	0	0	0	0	0	0	0	0	0	0
T2	0	0	0	0	0	0	0	0	0	0	0
T3	0	0	0	0	0	0	0	0	0	0	0

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