A Three-Phase Framework for Mapping Barriers to Blockchain Adoption in Sustainable Supply Chain

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Abstract

Purpose: Blockchain technology is one of the major contributors to supply chain sustainability because of its inherent features. However, its adoption rate is relatively low due to reasons such as the diverse barriers impeding blockchain adoption. The purpose of this study is to identify blockchain adoption barriers in sustainable supply chain and uncovers their interrelationships.

Design/methodology/approach: A three-phase framework that combines machine learning (ML) classifiers, BORUTA feature selection algorithm, and Grey-DEMATEL method. From the literature review, 26 potential barriers were identified and evaluated through the performance of ML models with accuracy and f-score.

Findings: The findings reveal that feature selection algorithm detected 15 prominent barriers, and random forest (RF) classifier performed with the highest accuracy and f-score. Moreover, the performance of the RF increased by 2.38% accuracy and 2.19% f-score after removing irrelevant barriers, confirming the validity of feature selection algorithm. An RF classifier ranked the prominent barriers and according to ranking, financial constraints, immaturity, security, knowledge and expertise, and cultural differences resided at the top of the list. Furthermore, a Grey-DEMATEL method is employed to expose interrelationships between prominent barriers, and to provide an overview of the cause-and-effect group.

Practical implications: The outcome of this study can help industry practitioners develop new strategies and plans for blockchain adoption in sustainable supply chains.

Originality/value: The research on the adoption of blockchain technology in sustainable supply chains is still evolving. This study contributes to the ongoing debate by exploring how practitioners and decision-makers adopt blockchain technology, developing strategies and plans in the process.

Keywords: Blockchain technology adoption, sustainable supply chain, barriers, BORUTA, machine learning, Grey-DEMATEL

1. Introduction

In today's world, blockchain technology (BCT) is gaining immense popularity as it has a tremendous impact on all industries, promoting transparency, and improving business processes (O. Ali et al., 2021; Fan et al., 2022). BCT can be considered an online and open-source encyclopedia or ledger that tracks all trade-related transactions and provides real-time updates (Subramanian et al., 2020). In simplest terms, it's a chain of blocks containing bits and pieces of transaction information (Farnoush et al., 2022; Yavaprabhas et al., 2022). In addition, the blockchain network contains multiple nodes, and two nodes can share transaction information, while one node broadcasts each transaction (Frizzo-Barker et al., 2020). If all the nodes have confirmed the correct information, then the transaction information is linked to the blockchain, and all the details of the transaction are accessible to all nodes in the network. BCT employs cryptography to ensure that the distributed ledger cannot be changed once distributed in the database and can be executed automatically using a script code (Dietrich et al., 2021; Subramanian et al., 2020). Although the applications and uses of BCT are more focused on the financial area, it also plays an important role in the non-financial areas (Lim et al., 2021). Furthermore, BCT contributes to a sustainable supply chain management (SSCM) in terms of environmental sustainability (Saberi et al., 2019). Therefore, as it is so versatile and diverse, industries are looking to adopt BCT to increase their reliability and success rate in trade.

Also today, sustainable supply chain (SSC) is attractive to researchers and supply chain experts (Shanker & Barve, 2021; Su et al., 2021) since it has environmental, social, and economic implications. Moreover, supply chain strategy of industries greatly affects its success (Khan et al., 2021). Therefore, it is crucial to strengthen supply chain performance as much as possible if the industry is to thrive. In addition, there are three types of movements that supply chain drivers can be involved in: product, information, and fund. However, SSCM is complicated due to the involvement of different types of movements, socio-economic and environmental impacts. Hence, the movements of the SSCM need to be made more transparent, more accessible, and more traceable than traditional supply chain to make it more sustainable and highly reliable. Additionally, the more transparent, traceable, and accessible the supply chain is, the more integrated it will. For SSCM, BCT provides transparency and traceability (Dietrich et al., 2021; Kayikci, 2022c) which ensures concerned sourcing and adherence to sustainable practices.

Moreover, supply chains become more reliable when BCT interacts with the supply chain (Chittipaka et al., 2022; Kouhizadeh et al., 2021). Furthermore, BCT automates SSCM procedures by putting smart contracts (Mane et al., 2024), mapping operations, and minimizing administrative overhead while retaining compliance with sustainability standards. Additionally, SSCM ensures sustainability by reducing waste as it gets precise information from BCT throughout the supply chain, enhancing environmentally friendly procurement, and optimizing distribution processes while reducing overproduction.

In addition, the modern supply chain is experiencing many challenges (Chaudhuri et al., 2021; Hussain et al., 2021) including the bullwhip effect caused by the information gap between the upstream and downstream, lack of trust hindering sharing of real information, difficulty in product tracking, and involvement of the third party like the bank, government, etc. However, BCT helps a SSC to overcome these problems by providing authentic information throughout the entire network and ensuring transaction security (Saberi et al., 2019). Furthermore, there has been an upward trend in the implementation of BCT in SCM by supply chain professionals and researchers in recent years (Moosavi et al., 2021). For example, startups such as BanQu in the food and agricultural industry, ChemChain in the chemical industry, EverLedger in the manufacturing sector, MonoChain in the apparel industry etc. handle BCT to establish sustainability in SCM (Kayikci et al., 2024). Also, already established companies like Walmart implemented BCT into their supply chain for food products, Maersk (a shipping company) utilized BCT to digitalize the tracking system of containers across the global supply chain (Thakker et al., 2024).

In addition, if the organizations can establish the implementation of BCT properly in their organization, then they have a great opportunity to increase service levels, maximize profits, and reduce risk by creating smart contracts and keeping information more confidential but available to everyone in the particular network. For example, Figure I presents a comprehensive sustainable supply chain model based entirely on BCT and focused on optimizing and securing each stage of supply chain. At the center, BCT stands as the core backbone that enables features such as accurate demand sharing, better communication throughout the process, and real-time transparency and cost savings. This supply chain model also ensures sustainability, carbon footprint tracking, and a customer-centric approach that makes the entire supply chain reliable. Integrating supply chain stakeholders increases efficiency, transparency, and sustainability in supply chain operations.

Moreover, the end-customer receives products with lifecycle information that enhances engagement in social and environmental aspects. Besides, a case study revealed that BCT promotes employee benefits, organizational enablement, and information security (Zheng & Lu, 2021). Furthermore, it also discovered that BCT works for a wide variety of industries and facilitates data sharing with a high degree of trust (O. Ali et al., 2021). Therefore, since the adoption of BCT boosts business processes, profits, management procedures, security, and profits (Frizzo-Barker et al., 2020), it is crucial for enhancing supply chain and trade reliability.

>INSERT FIGURE I HERE<

Chang & Chen (2020) aimed to investigate the new directions of BCT in SCM and analyzed 106 review articles to provide an overview of the use of BCT in SCM to make it more sustainable. According to their findings, they found that BCT has a positive impact on the supply chain to mitigate disruption and automate processes. Furthermore, BCT enhances the visibility of SSCM (Sunmola, 2021). Besides, BCT has the advantage of being distributed, thus reducing the risk of supply chain operations (Kouhizadeh et al., 2021). Again, a cross-sectional analysis of both the theoretical and the real-world aspects of BCT was conducted by Azzi et al. (2019), to establish the challenges of creating an efficient supply chain based on this technology, as well as to show how it can be integrated into the supply chain architecture to make it a high level of transparent, reliable, and sustainable. Furthermore, through the implementation of a blockchain-based SSC, it is possible to improve efficiency (Y. Wang et al., 2019), relationships, and reduce cost.

However, the adoption of BCT can enhance the supply chain and trade functionality, but this isn't a straightforward process (Bag et al., 2021). In this sense, companies should carefully manage the adoption and increase their absorptive capacity and technical capabilities to truly leverage BCT for their company. Furthermore, Supply chains are becoming increasingly globalized, making management and control more challenging (Saberi et al., 2019). Again, the literature reveals that BCT can improve supply chain operations through the adoption of BCT is a difficult endeavor. In addition, despite growing recognition of BCT's potential to improve supply chain transparency and traceability (Shujaat Mubarik et al., 2023), there is a notable lack of studies that systematically examine its implementation challenges and success factors across industries and geographic regions. Existing literature frequently focuses on theoretical frameworks and case-specific analyses (Tsolakis et al., 2021), resulting in a gap in comprehensive, cross-sectoral research that can provide actionable insights for a broader range of organizations seeking to implement blockchain for SSCM. In this sense, the specific objectives of this study are to:

- Identify and rank the barriers that may hinder BCT adoption, implementation, and upscaling in the SSC.
- Develop hierarchal cause-and-effect models to identify relationships among identified barriers.
- Provide practical insights into the applicability of this model with mapping the barriers.

This study aimed to address the following research questions (RQs).

RQ1: What are the prominent barriers to blockchain technology adoption in SSC?

RQ2: What are the interrelationships among those barriers?

A three-phase research methodology framework consisting of Machine Learning (ML) classifiers, BORUTA feature selection algorithm, and Grey-Decision-Making Trial and Evaluation Laboratory (Grey-DEMATEL) method is proposed to identify blockchain adoption barriers and reveal the relationships between them. In contrast, classification problems can be possible to solve very accurately through ML classifiers such as Random Forest, Decision Tree, Naïve Bayes, Logistic Regression, Support Vector Machine, and K-Nearest Neighbor with the high dimensional dataset (Morán-Fernández et al., 2022). Moreover, the feature selection algorithm has the potential to detect the prominent barriers, especially BORUTA since it selects relevance features based on statistical tests with multiple iterations (Spencer et al., 2020; Szul et al., 2021). Further, Grey-DEMATEL is one the most popular and potential Multi-Criteria Decision-Making (MCDM) techniques to visualize the interrelationships (Liu et al., 2021). Hence, this study used ML classifiers, BORUTA and Grey-DEMATEL to answer the RQs.

The paper proceeds with the following structure. Literature review and framework development are discussed in Section 2, and research methodology consisting of the methods in aiding the evaluation of the barriers and prioritization are presented in Section 3. The case study and results are presented in Section 4. Implications of the study are provided in Section 5. Finally, this study concluded in Section 6 highlighting the limitations and future research directions.

2. Research background

Increasing globalization makes the supply chain more complex (Bui et al., 2021; Saberi et al., 2019) and forces the adoption of SSCs rather than traditional ones. In addition, SSCs need to be more transparent and efficient and BCT can eliminate this cumbersome process. There is therefore an increase in the number of studies related to SSCM and BCT adoption in the literature. It has been identified by various researchers that BCT adoption is important as well as that adoption is hampered by several barriers. Several BCTs and SSCM-related studies are reviewed in the following section.

2.1 Blockchain technology: definitions and dimensions

BCT primarily get acquainted through the term "Bitcoin" in 2008, which was first introduced by Satoshi Nakamoto in the publication "Bitcoin: A Peer-to-Peer Electronic Cash System" (Adam & Dzang Alhassan, 2020). BCT has a great impact on business management, process management, credit transaction and industries such as agricultural, healthcare, manufacturing, aerospace, autonomous management and defense, port logistic, SCM and objectives such as cost, flexibility, and dependency (Ahmad et al., 2021; Idrees et al., 2021; Kshetri, 2018; Nasurudeen Ahamed & Karthikeyan, 2020; S. Wang et al., 2021; Yaqoob et al., 2021). Moreover, as we enter the Industry 4.0 (I4.0) era, BCT applications in management and business operations are expanding exponentially, and researchers are focusing more on how blockchain can be applied in management since these operations are very complex, and BCT can help to improve them (Choi et al., 2020; Luo & Choi, 2021; Tandon et al., 2021). Again, in order to automate business process management, it is necessary to integrate BCT and this can improve price management, reactive product management, project management, reactive power optimization, mutual trust, operational performances etc. in business processes and can collapse the conventional business models (Al-Rakhami & Al-Mashari, 2021; Chang et al., 2019; Danalakshmi et al., 2020; Dwivedi et al., 2020; Hargaden et al., 2019; Imeri et al., 2019; Queiroz et al., 2020; Viriyasitavat et al., 2020; Zhu & Kouhizadeh, 2019). Although, BCT has existed for over a decade (Nanayakkara et al., 2021), research indicates that its applications are relatively new (Wamba & Queiroz, 2020; Xu & He, 2024), especially in areas such as contract management, integration management, information management, stakeholder management. In addition to facing organizational, technical, and environmental challenges, adopting BCT is difficult due to legal uncertainty, ambiguous governance structures, insufficient infrastructure (Cheng et al., 2021; Lohmer & Lasch, 2020;

Chaudhuri et al., 2022; Clohessy & Acton, 2019). Additionally, a study revealed that operational challenges and technological challenges influence SCM to adopt BCT and it emphasizes SCM decision-making to achieve sustainable performance (Di Vaio & Varriale, 2020; Ghode et al., 2020; Kayikci et al., 2022c).

Moreover, manufacturing is one of the crucial stages of the supply chain and these industries are dependent on spare parts to maintain productivity, operations, etc. The distributed nature of BCT allows manufacturers to trace and track the ownership of spare parts (H. R. Hasan et al., 2020). Additionally, additive manufacturing is one of the greatest advances in digital production and BCT enables it by utilizing smart contracts and trace transactions in manufacturing, protecting businesses' intellectual property and personal data, and accelerating 3D printing as well as the flexible manufacturing network and shared factories (Alkhader et al., 2020; Klöckner et al., 2020). Besides, in industrial sectors, BCT enables digital twins to update virtual products data to reflect the latest physical products, and deliver communication via peer-to-peer, immutability, and transparency which helps in secured manufacturing through ensuring quality and traceability (Huang et al., 2020; Yaqoob et al., 2020; Chaudhuri et al., 2022). In addition, it is possible to improve the quality and efficiency of monitoring enterprise networks, and processes with different blockchain consensus algorithms. (Helebrandt et al., 2019; Vafiadis & Taefi, 2019). Furthermore, BCT-based platforms have a positive effect on production processes (Pan et al., 2020) and according to a recent study in China, companies' efficiency increased after deploying BCT and they run on average 42.24% below their maximum output levels before deploying this technology (M. R. Hasan et al., 2020). Again, an investigation of a survey on 306 supply chain experts from different industries has found that BCT impacts partnership growth and efficiency (Kim & Shin, 2019). Moreover, digital technologies are continually striving to improve product lifecycle management to take advantage of its versatile benefits but it's very hard to manage since it requires integrating and sharing information. BCT can improve the data management effectiveness, data quality, data sharing environment and product lifecycle management as well as can enhance the implementation of Vendor Managed Inventory model (Dasaklis & Casino, 2019; Holler et al., 2019; Liu et al., 2020; Wen et al., 2019).

2.2 Blockchain technology and sustainable supply chain

Nowadays BCT has numerous uses, especially in SSCM which is a highly complex process of the industries because it's tough to trace every stage of the product that passes through, so the popularity of BCT is growing as well as attracting a lot of interest in various industries such as developing nations are using BCT in their industries to maintain the sustainability of supply chains because of efficiency and security (Kayikci et al., 2022a; Kshetri, 2021; Sunny et al., 2020; Aich et al., 2019). Indeed, traditional supply chain faces challenges like a lack of transparency in tracking and coordination (Marques et al., 2024), leading to inefficiencies and trust issues among partners while BCT offers a decentralized, transparent ledger that ensures traceability and trust, offering a SSCM through improved accountability and reduced fraud risks. Furthermore, for achieving financial and social benefits, supply chain has a positive impact though it faces some issues (i.e., substantial data delays, inadequate information availability, unreliability, altering records by participants) and BCT is cutting edge solution to address these challenges and guarantees real-time information sharing for sustainable manufacturing with its features such as immutability, decentralization, transparency, etc. (Khanfar et al., 2021; Rejeb et al., 2019; Shakhbulatov et al., 2020; Tönnissen & Teuteberg, 2020; H. Wu et al., 2019; Leo et al., 2021). Using BCT, it is possible to trace the entire supply chain process and improve both the management and quality of the supply chain by ensuring efficiency and reliability in SCM by disseminating database transactions to ensure high levels of sustainability in SCM (ElMessiry & ElMessiry, 2018; Park & Li, 2021; Chaudhuri et al., 2022). Again, I4.0 powered supply chains are more sustainable with BCT and can enhance the visibility of the end-to-end process of global logistics SCM as well as can decrease operational and transactional costs, allows only valid transactions, improve product design, manage inventory properly, increasing efficiency, and reports the performance to the supply chain network (Cole et al., 2019; Esmaeilian et al., 2020; Juma et al., 2019; Schmidt & Wagner, 2019; Verhoeven et al., 2018). Besides, BCT-based SSCMs are more secure and suitable for international trade than traditional SCM, since hacking a blockchain is incredibly challenging (Howson, 2020; Valle & Oliver, 2021).

Moreover, BCT enhances sustainability in supply chains by allowing accurate tracking of materials movement from sourcing to the end consumer. It validates eco-friendly practices and encourages sustainable behavior. For example, in the fashion industry, BCT can authenticate organic cotton sourcing (Agrawal et al., 2021). In food and agriculture sector, it can verify fair trade certifications which builds trust sustainable practices (Lee et al., 2023). However, it can be concluded from the above discussion that while BCT is very promising for SSC applications in the near future, the acceptance rate is still low because many barriers exist (Kamilaris et al., 2019; Kouhizadeh et al., 2021). In addition to this, many researchers have identified several difficulties associated with the adoption of BCT in various industries, including healthcare, aerospace and defense, manufacturing, etc. According to them, these barriers are a high investment, complex integration, managerial commitment, privacy, lack of knowledge and expertise, customers awareness, cultural differences, scalability, tokenization, interoperability, large data traffic, privacy, etc. (Öztürk & Yildizbaşi, 2020; Vafadarnikjoo et al., 2021; Wasim Ahmad et al., 2021; Yaqoob et al., 2021). Again, according to a study on Indian SMEs found that technological barriers as the most influential barriers (Kaur et al., 2024). In addition, BCT adoption in the humanitarian supply chain gets interrupted by a lack of knowledge, high cost, employee training, etc. (Sahebi et al., 2020; Dohale et al., 2024). Since, multiple barriers prevent blockchain adoption, hence if it's possible to overcome these barriers a better SSC can be achieved.

2.3 Blockchain technology and sustainable supply chain management: Related studies in machine learning and feature selection algorithms

As we entered the I4.0 era, there has been an abundance of datasets globally (Sarker, 2021) and various methods available to gather the required datasets that we can use to train the ML models for the implementation of the BCT-based SSC. ML and blockchain-based SCM have the potential to achieve the technical sustainability of the supply chain and analyze the available database information critically (Wong et al., 2021; Yong et al., 2020). In addition, BCT and ML (another technique of Artificial Intelligence) aids decision-makers in understanding complex supply chain scenarios and facilitate SCM (Bertolini et al., 2021; Priore et al., 2019; Unal et al., 2021). Besides, ML can be used for a variety of purposes in SSCM, such as for forecasting sales and demands, detecting fraud transactions, maximizing profits, reducing bullwhip effects, and managing inventories (Boughaci & Alkhawaldeh, 2020; Feizabadi, 2022; Pallathadka et al., 2021; Shahbazi & Byun, 2021). Again, supply chains must be in a secure trade environment, and this can be achieved through a variety of emerging technologies such as blockchain, ML, and Internet of Things (IoT) (Hassija et al., 2021) and it was reported in a study on the smart pharmaceutical industry that ML and blockchain-based supply chain can track every step of the delivery process and recommend the best drugs to the customer. (Abbas et al., 2020). Furthermore, in 2020, Li et al. (2020) created a simulation for the advancement of SCM based on IoT, ML, and blockchain.

According to their findings, in the network of supply chains, this system has the potential to improve production efficiency, minimize risks, and provide a more reasonable and sustainable production management system. However, while ML can handle large datasets with many features or criteria, it assumes all features or barriers are relevant (Feltes et al., 2022). In addition, there are a lot of barriers to the deployment of the BCT. But all the barriers are not equally important, and it is impossible to mitigate all the barriers at a time. Since it is possible to obtain the prominent barriers through feature selection algorithms, being able to mitigate the crucial factors at first would be great. Feature selection removes irrelevant and redundant data while keeping the optimal subset of significant barriers or features (Odhiambo Omuya et al., 2021; Parmezan et al., 2021; Ramos-Pérez et al., 2022; L. Wang et al., 2021). Numerous algorithms are available for selecting features, including BORUTA, Chi-Square, Mutual Information, Recursive Feature Elimination, etc.

2.4 Multi-criteria decision-making application in blockchain technology and sustainable supply chain management

Methods of multi-criteria decision-making (MCDM) can be used to solve a selection problem involving a set of criteria and to find their interrelationships (Büyüközkan & Güler, 2021; Kumar et al., 2024). In order to identify the interrelationships, casual relationships or to reveal other informative relation, many researchers have used different types of MCDM approaches such as TISM, Fuzzy-DEMATEL, MICMAC, Best Worst Method, HFS, HFLTS, AHP, MUTIMURA, ISM-DEMATEL, Grey-DEMATEL, etc. (Büyüközkan & Güler, 2021; Chen & Lin, 2021; Farooque et al., 2019; S. S. Kamble et al., 2020; Moktadir et al., 2021; Munim et al., 2022; Shanker & Barve, 2021; Thanh, 2022; Yadav & Singh, 2020). Moreover, the Grey-DEMATEL methodology was employed to depict the causal relationships between essential success elements of the electronics manufacturing industry as well as to examine the relationships between several supply chain challenges which were faced by manufacturing organizations after the COVID-19 pandemic (Deepu & Ravi, 2021; Raj et al., 2022). Furthermore, the DEMATEL tool helps to identify the interrelationships between the crucial barriers (Boutkhoum et al., 2021) and is also used to identify BCT enablers in SCM (Agi & Jha, 2022). Again, the Grey-DEMATEL method was used to determine the enablers' causal relationship for the Indian electronic industry's SSC (Menon & Ravi, 2021). Furthermore, Khan et al. (2022b) were employed by Grey-DEMATEL to uncover the cause-and-effect relationship between drivers and barriers of circular economy implementation, and based on their findings, this MCDM tool is capable of analyzing these effects very precisely.

2.5 Research gap and contributions

Following a review of the above literature, it is evident that BCT is still in its infancy and the application of BCT in industry and business is increasingly significant (Kayikci et al., 2022b; Nayal et al., 2021). As well as this, the supply chain plays an important role in industrial activities as it brings together all the stages involved in the production and distribution of goods. However, SSCM is more suitable than traditional SCM, which is why modern industries are shifting from traditional supply chains to SSCs. Also, previous studies mostly focused on how BCT can affect on supply chain rather than exploring its potential contribution to sustainability. For example, Basrowi et el. (2024) studied to identify how BCT can improve the supply chain efficiency which has a impact on sustainability. Similar to this, Jackson and his colleagues (2024) tried to figure out how BCT can support to implement lean automation which will reduce the inefficiencies in the supply chain. Hence, if BCT can be integrated into a SSC, the industry's complex activities will become easier, as well as more transparent. Again, in SCM, BCT adoption is currently hindered by many barriers. So, some researchers have studied barriers to blockchain adoption for SCM (Etemadi et al., 2021; Karuppiah et al., 2021; Mathivathanan et al., 2021; Moretto & Macchion, 2022), but there is still a research gap pertaining to identify the major barriers to blockchain adoption for the SSCM. Also, there is a debate on the on findings of established researches. For example, Gupta et al. (2024) identified organization behaviour as a key barrier, while Ardiantono et al. (2024) identified cost as the most influential barrier. Moreover, most of the studies on blockchain adoption barriers used the MCDM method to extract key barriers, and there has limited study found that used ML and feature selection algorithms to find out the barriers to BCT adoption in SSCM. While feature selection algorithms can extract major features or barriers from wide datasets, ML is capable of handling large datasets efficiently (Batta, 2020). Although there are multiples feature selection algorithms but the barriers to implement in BCT in SSCM are interrelated (Yousefi & Tosarkani, 2024), indicating BORUTA as it can identify relevance features by comparing with shadow features (Manikandan et al., 2024). Again, to make this study more reliable we choose Grey DEMATEL to identify the interrelationships among the relevance barriers since it can handle uncertainty, ambiguity, and use qualitative approach to expose both direct and indirect relationships (Dixit et al., 2024). For example, studies carried out by Debnath et al. (2024) and Di Giorgio et al. (2024) in this field successfully identified interrelationships among factors with Grey DEMATEL.

In this regard, the contribution of this study can be summarized as follows:

i. It is proposed to compile an explicit list of barriers to BCT adoption for SSCs.

ii. A ML classifier is proposed to prioritize the prominent barriers.

iii. ML classifiers and the BORUTA feature selection algorithm are proposed for mapping the prominent barriers to BCT adoption for SSCs.

iv. The Grey-DEMATEL approach is proposed to identify the interrelationship among the prominent barriers.

v. Identified barriers from this study can facilitate industries to adopt BCT in the SSC by mitigating these barriers.

3. Methodology

In order to accomplish the research objectives and prioritize and map the prominent barriers to BCT adoption in SSCM, a three-phase research methodology framework, illustrated in Figure I, was proposed. In the first phase, potential barriers are selected and collected by experts' decisions. As part of the second phase, the potential barriers pass in the ML classifiers. After that, in the second phase, BORUTA identifies the prominent barriers and prioritize them with an appropriate ML classifier. In the third phase, Grey-DEMATEL addresses the interrelationships among prominent barriers to mapping them. However, all the mathematical background of ML, FS, and Grey DMATEL are mentioned the Appendix B.

>INSERT FIGURE II HERE<

3.1 Identification and categorization of barriers

Firstly, an extensive literature search was conducted in literature databases such as “Google Scholar”, “Scopus”, and “Web of Science” using the mentioned keywords strings in Figure II to identify barriers to adopting BCT for SSCM. Following that, the inclusion criteria enabled the discovery of research articles relating to SSCM and BCT. Afterward, 38 barriers were found regarding BCT, SSC, green supply chain, etc. whereas only 26 barriers were selected as potential barriers for this study since they pertain to blockchain adoption in SSCM and are relevant to our research objectives. In addition, the following dimensions are widely known for categorizing the barriers to the adoption of blockchain in SSCM: technical, organizational, environmental, economic, and social (Kouhizadeh et al., 2021; Öztürk & Yildizbaşi, 2020; Saberi et al., 2019). Hence, the selected barriers are distributed into the five types of dimensions and the inclusion of the potential barriers in each dimension has been taken based on the extensive literature. All the potential barriers are presented in Table A1 (See Appendix A).

>INSERT FIGURE III HERE<

4. Case study and results

4.1 Case companies and expert background

For this study, we have collected data from the experts in global supply chain and blockchain across a wide range of industries. Experts in the study have different profiles, levels of education, levels of experience, and were from a variety of industries intentionally to achieve homogeneity in ensuring that the outcomes can be generalized to any industry.

We sent a survey containing three parts to each expert **(**see Appendix C**)**. In the first part, the demographics of the experts were collected and found in Table I. Second part explains the researchers' selected barriers to BCT adoption in SSCM, which can be viewed as independent variables for selecting the prominent barriers. In the third part, each expert was asked how straightforward it would be for SSC practitioners to adopt blockchain if the barriers they focused on were removed to collect the target variable. In total, 312 experts from different types of global industries were contacted via email and LinkedIn, and 210 of them participated. Previous studies considered 8-14 experts' decisions to identify the crucial barriers to blockchain adoption (Öztürk & Yildizbaşi, 2020; Vafadarnikjoo et al., 2021), whereas our study considered a wider range of experts' decisions. In addition, large datasets can also be efficiently handled using ML (Batta, 2020). Therefore, we believe that 210 experts for this study is justified.

>INSERT TABLE I HERE<

4.2 Barrier identification and finalization for blockchain technology adoption in sustainable supply chain

In the first phase, all the potential barriers are collected from the literature and the data was considered based on SCM and blockchain experts' judgments to identify and prioritize the prominent barriers.

In the second phase, all of the initially selected barriers have been selected as independent variables for ML classifiers (See Appendix B) to identify prominent barriers, and straightforwardness to adopt BCT have been used as the target variable. Hyperparameters are necessary for ML, and they can regulate its behavior (J. Wu et al., 2019). The independent variables are passed into ML classifiers with varied hyperparameters to get the maximum accuracy and f-score. Besides, for this study, 80% of the dataset was used to train the ML models with Google Colab and Python. The KNN classifier was trained with p = 2 in Equation (20) with the hyper-parameters "n_neighbors = 5" and "metric = Minkowski". To kernelize the SVM classifier, C = 1 is utilized along with the "kernel = rbf" hypermeter. In addition, for LR, "intercept_scaling = 1" and "solver = lbfgs" are specified. The "gini" criterion is applied to decision tree classifiers. The RF classifier was trained with "n_estimators = 1000" and “criterion = gini”. As a result of all the hyperparameters of the ML classifiers, Table II presents the accuracy and f-score values before applying the feature selection algorithm. As per our expert's decision, the RF classifier provided the best accuracy and f-score with 88.09 % and 86.98 % respectively among all of the ML classifiers.

>INSERT TABLE II HERE<

Again, in the second phase, BORUTA was performed to separate the irrelevant and prominent barriers to BCT adoption within SSCM as per the significance of the barriers. Figure III generated in the R environment with the BORUTA package in which the importance of each feature or barrier is indicated on the Y-axis, while barriers are shown on the X-axis. Additionally, shadow features are shown in blue box plots according to their Z-score for selecting prominent barriers. In order to identify the importance of each feature or barrier, BORUTA creates shadow features or shadow barriers. All shadow features are shadow-Min, shadow-Mean and the shadow-Max. Each barrier along with the red box plot has much lower Z-scores than shadow-Max, so they are deemed ineffective barriers to BCT adoption in an SSC. The yellow box plot represents tentative prominent barriers, and the green box plot corresponds to prominent barriers for BCT adoption. Iterations of the BORUTA algorithm were conducted multiple times to obtain these prominent barriers. A summary of the selection results of Figure III can be found in Appendix Table D-1. In this case, according to the BORUTA, out of 26 features, 5 are rejected, 6 are tentative, and 15 are confirmed. In Appendix Table D-1**,** the column Norm-Hits stands for the number of hits normalized by the number of important source runs. According to BORUTA, the most prominent barriers to integrate BCT in SSCM are security (T5), Immaturity (T3), Financial constraints (E1), Managerial commitment (O2), etc.

>INSERT FIGURE IV HERE<

In the same phase, ML classifiers are again applied with the same hyper-parameters that were used before the feature selection to validate the BORUTA algorithm's decision. The independent variables here are only the BORUTA selected prominent barriers and the dependent variable remains unchanged. Table III summarizes the accuracy and f-scores of all ML classifiers considering prominent barriers as the independent variables.

>INSERT TABLE III HERE<

Again, we can see that in Table III, RF provides maximum accuracy of 90.47 % and 89.17 % of f-score among all the ML classifiers. In the RF, numerous decision trees are generated in order to create an accurate classification. Accordingly, once the irrelevant barriers are removed, accuracy score and f-score increase by 2.38% and 2.19% respectively. It is therefore justified that the BORUTA algorithm has selected the prominent barriers.

Again, it is important to note that BORUTA does not provide only the ranking of the selected independent variable subsets by default (Alsahaf et al., 2022). Hence, the RF classifier once again selected to prioritize BORUTA selected prominent barriers since the RF classifier had previously achieved the maximum score of performance metrics. In addition, the model with the highest accuracy and f-score gained is the most appropriate model for classification (R. C. Chen et al., 2020). In order to determine the importance of each feature or barrier, RF used 'feature_importances_'. Based on the RF analysis, Table IV lists the prominent barriers in order of importance. However, there are some variations between the rankings determined by BORUTA algorithms and the RF classifier. For instance, the BORUTA algorithm identifies security (T5) as the most crucial barrier, whereas RF emphasizes financial constraints (E1). There may be a difference here because RF ranks only prominent barriers, while BORUTA ranks all barriers. Thus, the ranking determined by RF is more accurate since it ranks prominent barriers only.

Lastly, in the third phase, Grey-DEMATEL reveals the interrelationships between prominent barriers selected by the RF. Through interrelationships, it is possible to uncover the real barriers that play a crucial role from backstage in the adoption of BCT and aid in mapping them. The interrelationships among the prominent barriers briefly discussed in Section 4.4.

Overall, according to our study Immaturity (T3), Security (T5), Knowledge and expertise (O5), Lack of technological tools (E4), Managerial commitment (O2), and Customers' awareness (EN3) are also prominent barriers to adopting BCT. Further, some studies have also identified managerial commitment, lack of knowledge, immaturity, cultural differences, technological limitations, and customer awareness as prominent barriers to BCT (Farooque et al., 2020; Öztürk & Yildizbaşi, 2020) but the findings of our study are different from them. For example, financial constraints have not been reflected as one of the top barriers in previous studies. The study also identified immaturity and security as more significant barriers than cultural differences and managerial commitment, whereas previous studies identified cultural differences and managerial commitment as the top barriers (Bag et al., 2021; Vafadarnikjoo et al., 2021). Further, some studies found lack of knowledge and technological tools as the top barrier (Mathivathanan et al., 2021; Sahebi et al., 2020), which differs from ours. Based on experts' opinions, this is possible since the study covered multiple industries and considered a large number of decision-makers.

>INSERT TABLE IV HERE<

4.3 Cause and effect group of BCT adoption barriers

To identify the causal relationship, Grey-DEMATEL is implemented following the steps as discussed in Appendix B.4. To determine the overall grey direct relationship matrix, Table V presents a summarized direct relationship matrix. There are four types of matrices: the degree of prominence and degree of effect (Table VI), the total correlation matrix (Appendix Table E-3), the grey direct relationship matrix (Appendix Table E-1), and the normalized matrix (Appendix Table E-2). Following this, Figure IV categorizes the prominent barriers into two groups including:

cause, effect. The cause group consists of barriers with positive relation values, and the effect group consists of barriers with negative relation values.

In the cause group there are six barriers, and it is possible for these barriers to create impacts on other 9 barriers of effect group to redeem BCT adoption in a SSC. Identified critical causes are cultural differences (O3), inadequate knowledge and expertise (O5), negative perception (S1), unwillingness to adopt new systems (O6), interoperability (T7), and information disclosure policy (O1). It is imperative for companies to become more aware of blockchain and promote employee awareness of the technology, as both developed and developing countries consider it a necessity (Khan et al., 2022a). It will allow organizations to decrease cultural differences among them and reduce another cause barrier O6. Despite the long-term benefits of BCT implementation, organizations are still unaware of the benefits, so it is important to train employees about BCT adoption through professionals to increase expertise on BCT as well as reduce negative perceptions. (Dwivedi et al., 2022; Kurpjuweit et al., 2021). As illustrated in Figure IV, the barriers to effect groups include managerial commitment (O2), integrating sustainable practices (EN4), lack of technological tools (E4), access (T1), customer awareness (EN3), security (T5), integrating sustainable practices (O4), immaturity (T3), and financial constraints (E1). Rather than influencing others, managerial commitment (O2), integrating sustainable practices (EN4), and technological tools (E4) are mostly influenced by the causal group. It is thus necessary to overcome barriers under the cause group to have an influential response from the effect group.

>INSERT TABLE V HERE<

>INSERT TABLE VI HERE<

>INSERT FIGURE V HERE<

4.4 Interrelationships among the prominent barriers to adopting BCT

In Figure V, the interrelationships among the prominent barriers are illustrated. The threshold value of 0.836 is determined by implementing Grey-DEMATEL to establish the interrelationships among the prominent barriers. According to the findings, access (T1) and information disclosure policy (O1) have more interaction with other prominent barriers. However, financial constraints (E1), immaturity (T3), and security (T5) appear to be the top three most important barriers in Table IV, although, surprisingly, they don't have many interrelationships with other prominent barriers.

The identified barriers in a study by Farooque et al. (2020) also differed from the cause barriers. This indicates that, the barriers with the greatest interrelationship with other barriers should be mitigated before the top ranked barriers.

>INSERT FIGURE VI HERE<

5. Discussion

In this study, BORUTA identified security (T5), financial constraints (E1), and collaboration and communication (O7) as crucial barriers to implement BCT in SSCM. BORUTA provides insights based on important scores, which compare real features with shadow features or randomly permuted versions of the original features. In this study, BORUTA's iteration identified security (T5) as the most essential barrier, with an outstanding Mean IMP (importance) value of 15.633. Financial limitations (E1) represented the second most significant barrier, with a Mean IMP score of 13.175. Barriers such as negative perception (S1), ethical industry involvement (EN2), and external stakeholders' involvement (E3) have been rejected due to inadequate scores. This approach ensures that only truly significant features are selected, reducing the risk of overfitting. On the other hand, analysis of Grey-DEMATEL, factors such as immaturity (T3) and financial constraints (E1) emerged as interrelated due to their strong influence (Ri+Ci) and interdependencies (Ri-Ci) with other barriers and organizational outputs, highlighting these as critical issues to address. Moreover, factors with lower values (Ri+Ci and Ri-Ci) may indicate lesser influence or dependency within the network of barriers and organizational factors studied, suggesting they may have less impact on the overall system dynamics. However, to ensure a robust outcome from the BORUTA, we carefully selected parameters such as n_estimators, max_depth, and min_samples_split to reduce overfitting and reveal accurate results. Again, rigorous validation helped to decrease the method's sensitivity to parameter settings. It is also necessary to note that the findings of this study have a relation with Sustainable Development Goals (SDGs). Ensuring robust security (T5) contributes to SDGs 9 (Industry, Innovation, and Infrastructure) and 16 (Peace, Justice, and Strong Institutions) by improving transaction integrity and institutional transparency. Again, addressing financial constraints (E1) aligns with SDGs 8 (Decent Work and Economic Growth) and 17 (Partnerships for the Goals which promotes economic growth and global cooperation. Another key barrier communication (O7) also supports SDGs 9 and 17, fostering innovation and sustainable industrialization through effective partnerships. As a practical example, Walmart's use of BCT to track food supply chains eliminates barriers such as interoperability (T7) and information disclosure (O1), increasing transparency and sustainability (Mohammed et al., 2023, Thakker et al., 2024). However, based on the findings of this study, future research could focus on how targeted strategies can be developed to address the identified critical barriers in this study such as creating tailored training programs to enhance knowledge and expertise (O5), designing frameworks to manage cultural differences (O3) and redeem negative perceptions (S1). Again, for instance, companies such as TradeLens, established by IBM and Maersk, are already addressing these issues by improving supply chain transparency and security (T5) through BCT while providing scalable and cost-effective solutions to decrease financial barriers (Sedej et al., 2022). Additionally, future studies could explore solutions to improve interoperability (T7) and policies to balance information disclosure (O1). Also, initiatives such as promoting sustainability and tracking the changes with BCT can add a paramount value. For example, IKEA used BCT for tracking sustainable sourcing and renewable energy investments which not only supports transparency and accountability but also ensures that every step in their supply chain adheres to sustainability standards (García-Arca et al., 2024).

6. Managerial and Practical implications

In this study, the identified prominent barriers to adopting BCT in SSCM offers some crucial implications to the industry managers for adopting BCT. As this study considered many industries in its search for barriers to BCT adoption in the supply chain, it can be used to assist the managers of almost all industries in implementing BCT. Several implications are also recommended to the managers of various industries based on the research findings including:

First, looking into the findings of the study reveals that the top three major barriers to blockchain adoption are financial constraint (E1), Immaturity (T3) and Security (T5). The deeper analysis reveals that the major cause of all three factors is unwillingness to adopt new systems (O6). So, the real barrier behind blockchain adoption is a firm’s lack of willingness to adopt new systems. It implies that managers must first work on the organizational readiness to create willingness among various stakeholders for adoption of BCTs. It will start from gaining the demonstrated sponsorship of top management to adopt BCTs. There are numerous examples where the process of technological adoption was not successful as top management’s demonstrated sponsorship was absent. If top management is convinced and willing to adopt blockchain, the constraints like finances, lack of access and immaturity could be easily overcome. Similarly, for increasing willingness to adopt blockchain, employees need to be oriented about blockchain and its potential benefits. Another aspect of readiness is the processes capability and capacity to adopt block chain. A firm having employed heterogeneous hardware and software, with varying quality, speed, and reliability, first needs to work on its technological readiness by standardizing and integrating various software and hardware technology. In short, the first step toward adoption of BCT is creating the need and willingness among various stakeholders about it.

Interoperability is another important aspect that a manager must investigate. If the existing processes are flexible and robust enough to accommodate the BCTs, the transformation becomes much easier and rapid. This is one of the reasons that interoperability is stressed while discussing blockchain adoption. Further managers must also look for changing the perception of the people about blockchain. Our results reveal that negative perception (S1) significantly impedes the blockchain adoption directly and by creating issues of security and financial constraint. Managers develop a positive perception of people by demonstrating how BCT could influence the various performance indicators.

Although developing willingness among top management teams will help a firm to overcome financial constraint, a deliberate effort would be required by industry managers to enhance their funds to receive long term benefits from BCT (Öztürk & Yildizbaşi, 2020). The Grey-DEMATEL outcome assists managers in understanding the interrelationships between the barriers, thereby revealing their root causes (Karuppiah et al., 2021). Managers may find strategies to incorporate BCT in the SSCM by identifying and solving the root causes of these barriers.

According to this study, lack of organization policies, lack of customer awareness, knowledge and expertise are also reflected as prominent barriers. By offering training programs, redeeming negative perception, developing organizational policies, increasing customer awareness programs and motivating employees to adopt BCT, empowering the workforce, industry experts can assist companies in lowering the barriers to adopting BCT (Chowdhury et al., 2022). Likewise, companies also work on increasing their absorptive capacity and technical capabilities to truly leverage BCT for their company.

Lastly, managers can use the present study to explore and examine prominent barriers in numerous categories, including technical, organizational, economic, environmental, social barriers. Again, the ranking of the prominent barriers helps managers to understand the severity of each barrier, and which needs to be reduced most initially to successfully implement BCT, based on their industry (Kaur et al., 2022). They can apply this methodology in their organization to find out the prominent barriers to adopt BCT in an SSC.

7. Conclusions and future research directions

One of the most critical implications now is global sustainability. There are numerous challenges in developing sustainability in industries including technological and organizational issues (Gupta et al., 2020). Increasingly, the majority of developed and international organizations have started implementing emerging technologies like blockchain to combat this problem (Karuppiah et al., 2021). However, many industries are having difficulty adopting this technology. In order to overcome this, the main objective of our study was to identify the prominent barriers and the interrelationships among the prominent barriers that hinder the adoption of BCT in SSCs. We analyzed 26 potential barriers under five categories using the BORUTA algorithm to identify the most prominent barriers. Data was taken from 210 experts of various types of industries including FMCG industry, garments industry, automotive industry, etc. The analysis revealed in total 15 barriers as prominent barriers including financial constraints, immaturity, security, knowledge, and expertise. Further, ML classifiers were utilized to validate the BORUTA algorithm's decision. A Grey-DEMATEL analysis was performed again to identify the cause-and-effect groups of prominent barriers, as well as visualize their interrelationships. However, this study's findings and the literature differ significantly. Furthermore, through this study, managers are enabled to see the ranking of prominent barriers as well as the barriers that influenced and influenced them. This study provides a hybrid methodology to identify the prominent barriers to adopt BCT in a SSC. As opposed to improving traditional SSCM, managers can mitigate these prominent barriers by implementing new policies and appropriate measures (Farooque et al., 2020).

However, as with the other studies, this study has some limitations. This study considered few potential barriers from a social perspective compared to other aspects. Future studies can focus on social aspects and barriers which hinder BCT adoption. Again, this study considered only a variety of industries rather than focusing on a particular industry. In future studies, a case study can be analyzed considering any particular industry. In addition, many other feature selection algorithms such as Chi-square, Recursive feature elimination, PCA, LDA, etc. can be used to identify the prominent barriers. Moreover, in future, studies can include Fuzzy Inference System, AHP or any other tools to expose the interrelationships.

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Appendix A

Table A1: Identification of initial barriers to adopting BCT for sustainable supply chain.

Dimensions	**Barriers**	**Definitions**	**Supported References**
Technical Barriers	Access (T1)	Access to the Internet and Information Technology (IT) infrastructure of the organization is very limited.	(Kouhizadeh et al., 2021; Vafadarnikjoo et al., 2021; Chaudhuri et al., 2022)
	Immutability (T2)	The concept of immutability suggests that records cannot be removed from ledgers. A record that is incorrectly entered into the blockchain can be corrected, but its history will always be stored.	(S. Kamble et al., 2019; S. S. Kamble et al., 2020; Paliwal et al., 2020; Chaudhuri et al., 2022; Kayikci & Subramanian, 2022)
	Immaturity (T3)	BCT is immature in different aspects such as changing the number of blocks.	(Bag et al., 2021; Kouhizadeh et al., 2021; Vafadarnikjoo et al., 2021; Kayikci & Subramanian, 2022)
	Usability (T4)	BCT is not as user-friendly as existing systems.	(Öztürk & Yildizbaşi, 2020)
	Security (T5)	The availability of sensitive information and data may be subject to security concerns.	(Casino et al., 2019; Paliwal et al., 2020; Y. Wang et al., 2019; Chaudhuri et al., 2022)
	Complexity (T6)	Compared to existing systems, BCT is much more complex.	(Öztürk & Yildizbaşi, 2020; Kayikci & Subramanian, 2022)
	Interoperability (T7)	Exchange capabilities of the system with BCT.	(Öztürk & Yildizbaşi, 2020; Kayikci & Subramanian, 2022)
Economical Barriers	Financial constraints (E1)	There is a high cost associated with the implementation of BCT.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021)
	Lack of research and development (E2)	In many industries, BCT is being delayed by a lack of research and development units and increased cost of implementation as well as maintenance.	(Öztürk & Yildizbaşi, 2020)
	External stakeholders' involvement (E3)	The lack of support for sustainable practices and BCT adoption by external stakeholders such as NGOs and communities.	(Bag et al., 2021; Kouhizadeh et al., 2021; Paliwal et al., 2020; Vafadarnikjoo et al., 2021)

	Lack of technological tools (E4)	BCT cannot be adopted due to a lack of technological tools.	(Kouhizadeh et al., 2021; Saberi et al., 2019; Kayikci et al., 2022c; Chaudhuri et al., 2022)
Environmental Barriers	Lack of government policies (EN1)	There is a reluctance on the part of the government to impose regulations on BCT adoption.	(Kouhizadeh et al., 2021; Saberi et al., 2019; Vafadarnikjoo et al., 2021; Kayikci et al., 2022c)
	Ethical industry involvement (EN2)	There are few ethical and safe practices in the industries.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021)
	Customers' awareness (EN3)	Customers are unaware that blockchain can be used in sustainable supply chain management because of a lack of knowledge and awareness.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Vafadarnikjoo et al., 2021)
	Sustainable practices integration (EN4)	Embracing sustainability practices and blockchain in supply chain management can be challenging.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021)
	Risks of cyber-attacks (EN5)	As a result of cyber-attacks, information can leak, resulting in the adoption of BCT being hindered.	(Vafadarnikjoo et al., 2021; Kayikci et al., 2022c)
	Information disclosure policy (O1)	Insufficient information disclosure policy among the supply chain partners.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021)
	Managerial commitment (O2)	Support and commitment of the top-level managerial section are absent.	(Bag et al., 2021; Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021)
	Cultural differences (O3)	It may be difficult for BCT to be adopted by different supply chain partners due to cultural differences.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021)
	Lack of organizational policies (O4)	Organizations must develop new policies to implement BCT in sustainable supply chain management.	(Saberi et al., 2019; Vafadarnikjoo et al., 2021)
	Knowledge and expertise (O5)	The current workforce lacks knowledge and expertise.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021; Kayikci et al., 2022c)

Organizational Barriers	Unwillingness to adopt new systems (O6)	Adapting new systems would require changing legacy systems, which can hinder blockchain adoption.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021; Kayikci et al., 2022c)
	Collaboration and communication (O7)	Supply chain collaboration and communication issues must be digitized to adopt BCT.	(Bag et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Vafadarnikjoo et al., 2021; Kayikci et al., 2022c)
Social Barriers	Negative perception (S1)	Blockchain adoption intentions may be lower if public perceptions are negative.	(Kouhizadeh et al., 2021; Vafadarnikjoo et al., 2021; Chaudhuri et al., 2022)
	Wasted resources (S2)	BCT consumes a large amount of electrical energy to operate.	(Öztürk & Yildizbaşi, 2020)
	Lack of rewards and encouragement programs (S3)	Programs that reward and encourage BCT usage may increase its adoption.	(Kouhizadeh et al., 2021; Paliwal et al., 2020; Saberi et al., 2019; Kayikci et al., 2022c; Chaudhuri et al., 2022)

B.1 Machine learning classifiers

ML classifiers are widely used in classification problems and learning based on training data. In addition, ML classification techniques can easily recognize classes precisely for a given dataset (Thakkar & Lohiya, 2021). The following section will discuss different types of ML classifier intuitions.

B.1.1 Naïve Bayes

Naive Bayes is a probabilistic approach that can be used to classify features. This ML classifier algorithm follows the Bayes theorem and assumes that the set of features is independent (Ehatisham-ul-Haq et al., 2021).

According to the Bayes theorem,

$$P(M|N) = \frac{P(M) * P(N|M)}{P(M)} \tag{1}$$

Where $P(M)$ and $P(N)$ are the probability of occurring events M and N respectively. $P(M|N)$ is the probability of occurring M if N has already happened.

Let B be the variable of independent features for identifying the prominent barriers to adopt BCT, and D be the target variable.

Therefore, B can be written as $B = (B_1, B_2, B_3, \ldots\ldots B_n)$. Where $B_1, B_2, B_3, \ldots\ldots B_n$ represents each feature or barriers to adopt BCT in sustainable supply chain management.

$$P(B|D) = \frac{P(B) * P(B|D)}{P(B)} \tag{2}$$

Using the chain rule,

$$P(D|B_1, B_2, B_3, .., B_n) = \frac{P(D) * P(B_1|D) * P(B_2|D) * P(B_3|D) * \ldots\ldots . P(B_n|D)}{P(B_1) * P(B_2) * P(B_3) * \ldots . P(B_n)} \tag{3}$$

From Equation (3),

$$P(D|B_1, B_2, B_3, .., B_n) = \frac{P(D) * \prod_i^n P(B_i|D)}{P(B_1) * P(B_2) * P(B_3) * \ldots . P(B_n)} \tag{4}$$

In Equation (4), the denominator of that equation will remain static for all the cases. Therefore,

$$P(D|B_1, B_2, B_3, \ldots\ldots B_n) \propto P(D) * \prod_i^n P(B_i|D) \tag{5}$$

This Equation (5) is commonly used to classify predictive modeling problems and is often referred to as the Naive Bayes classifier.

B.1.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised ML algorithm used in the case of classification and regression in numerous fields (L. Ali et al., 2021; Piccialli & Sciandrone, 2022). SVM creates a decision plane that sets the decision boundaries for different events and establishes a set of hyperplanes as members of other classes, then used for classification (Pal & Kumar, 2021).

Let p be a set of objects, and M is the feature objects of the barriers to adopt BCT such that $M€ R$. So that the feature object can describe as $M = \{m_1 , m_2 , m_3 , \ldots\ldots, m_p\}$

Furthermore, assume that each object belongs to one class of two so that the class members can be written as $n = \{+1, -1\}$.

Now, the classification function of the SVM can be written as,

$$n_i \; or \; f(m) \; = \; Q^T m \; + \; d \tag{6}$$

Here, Q^T is the transposed vector of the weights, and d is the intercept.

Again, the geometrical distance between the closest data point of a class and the boundary line can be written as,

$$Distance \; = \; \frac{1}{||Q||} \tag{7}$$

Therefore, the interval between the classifications is $\frac{2}{||Q||}$ and the optimization function will,

$$\frac{||Q||^2}{2} + C_i \sum_i^k \zeta_i \text{ such that } n_i(Qm_i + d_i) \; \geq \; 1 - \; \zeta_i \tag{8}$$

Here, $i \; = \; 1,2,3, \ldots., K$ (Training sample size), C_i is the number of errors and ζ_i is the value of each error. It's possible to maximize the hyperplane margin and minimize misclassification by tuning C.

The dual problem of the Equation (8) is possible to establish using Lagrange Multipliers as follows:

$$\frac{1}{2}\sum_i^k \alpha_i \alpha_j n_i n_j m_i^T m_j - \sum_i^k \alpha_i \; such \; that, \{\sum_i^k y_i \alpha_i = 0 \tag{9}$$

$$0 \leq \; \alpha_i \leq \; C \text{ here, i = 1,2,3, …, k}$$

Here, α_i represents the Lagrange multiplier. So that, the weight vector can be defined as follows:

$$Q \; = \; \sum_i^k y_i \alpha_i m_i \tag{10}$$

Therefore, the function of the SVM is as follows:

$$f(m) \; = \; sign(\textstyle\sum_i^k \alpha_i n_i m_i^T \; + \; d_i) \tag{11}$$

Here, $sign$ () is a mathematical function that returns a + or - based on the numeric value of the argument.

B.1.3 Logistic Regression (LR)

Logistic Regression (LR) is a probabilistic model built from instances of a class's probabilities which is potential for multivariable control (Sun et al., 2021). LR applies the logistic or sigmoid function to each dataset class to calculate these probabilities.

Let M be the variable of independent features or barriers to adopt BCT in sustainable supply chain, and P be the target variable to identify the prominent barriers. So that, M can be represented as $M = \{m_1, m_2, m_3, \ldots, m_n\}$ such that $M \in R$ and $P = \{1, -1\}$.

So, the function of LR can be written as,

$$P \; or \; f(m) = S^T m + v \tag{12}$$

When the intercept v passes through the origin. As a result, $v = 0$. Now, substituting the value of v in Equation (12),

$$P \; or \; f(m) = S^T m \tag{13}$$

Now, from the linear algebra distance function,

$$\frac{S^T m_i}{||S||} \tag{14}$$

By considering $||S||$ as a unit value and substituting it into Equation (14),

$$P_i = S^T m_i \tag{15}$$

Based on the Equation (15), there are some cases possible as follows:

CASE 1: $P_i = 1 \; and \; S^T m_i > 0$

For this case, the distance will $P_i * S^T m_i > 0$

CASE 2: $P_i = -1 \; and \; S^T m_i < 0$

For this case, the distance will $P_i * S^T m_i > 0$

CASE 3: $P_i = -1 \; and \; S^T m_i > 0$

For this case, the distance will $P_i * S^T m_i < 0$

CASE 4: $P_i = 1 \; and \; S^T m_i < 0$

For this case, the distance will $P_i * S^T m_i < 0$

CASE 1 and CASE 2 will give the distance of data points that are correctly classified among these four cases. Again, CASE 3 and CASE 4 will provide the distance of misclassified data points.

So that the sum of the distance of all data points will be an optimized function for the LR, and this can be written as,

$$Optimized\ function = \sum_{i}^{k} P_i S_i^T m_i \tag{16}$$

In LR, our primary goal is to maximize the distance to evaluate the best fit line. It can be done by maximizing the Equation (16). Therefore, the optimized function will,

$$Optimized\ function = argmax \sum_{i}^{k} P_i S_i^T m_i \tag{17}$$

Now, it is possible to create the best fit line from the Equation (17), but this equation cannot classify the data points accurately when outliers begin. A function named the "Sigmoid" is generally used in LR to eliminate this problem. The sigmoid function can be represented as,

$$Sigmoid\ function, f(x) = \frac{1}{1 + e^{-x}} \tag{18}$$

Therefore, the optimized final function will,

$$Optimized\ function = argmax \sum_{i}^{k} \frac{1}{1 + e^{-(P_i S_i^T m_i)}} \tag{19}$$

Equation (19) can take the outliers in range. So that, by using Equation (19), LR can classify the data points accurately for identifying the prominent barriers to BCT adoption**.**

B.1.4 K-Nearest Neighbor (KNN)

K-Nearest Neighbor (KNN) is a supervised ML algorithm where different types of neighbors are treated equally with uniform weight (Bustamante-bello et al., 2022). In this algorithm, K defines the number of neighbors in the algorithm.

Let M be the variable of independent features or barriers, and P be the target variable for selecting the prominent barriers. So that the pattern M can be represented as $M = \{m_1,\ m_2,\ m_3, .., m_n\}$. Again, the set of labels, $W = \{w_1,\ w_2,\ w_3, .., w_n\}$.

Therefore, $\{(m_1, w_1), (m_2, w_2), (m_3, w_3), .., (m_n, w_n)\}$ are the set of observations for BCT barriers identification of T dimensional pattern $M = \{m_i\}_i^n \subset R^T$ and the class of label is $W = \{w_i\}_i^n \subset R$.

KNN aims to learn a function that can predict the class of W'' by using the unknown pattern M'' for K data points. KNN always considers M' as the nearest pattern for the target. Therefore, one should apply the Minkowski metric (P-norm) in R^T. Now,

$$||m' - m_j||^p = \left(\sum_{i=1}^{T} |(m_i)' - (m_i)_j|^p\right)^{\frac{1}{p}} \tag{20}$$

In Equation (20), when the value of $p = 1$, it will be considered as Minkowski distance. Again, when the value of $p = 2$, it will consider the Euclidean distance. Since KNN classifies based on the value of distance, Equation (20) is the function of KNN for the prediction.

B.1.5 Decision Tree

There are many different algorithms for classifying data into different categories, but decision trees are the simplest and most powerful algorithms for doing this (Gao & Elzarka, 2021). The decision tree constructs a tree-based model by splitting the nodes. Each of the features or potential barriers in the decision tree represents a node. With the value of entropy and information gain, the decision classifies the data into different classes. The function of entropy for each node can be written in Equation (21) as,

$$E\ (g)\ =\ -\sum_{i}^{b} P_g(b_i) log_2 P_g(b_i) \tag{21}$$

Here, b represents the number of classes.

In addition, the information gain computes the value of entropy from the node to a leaf of a decision tree. The function of information gain can be written in Equation (22) as,

$$IF\ (g,t)\ =\ E\ (g)\ -\ \sum_{i}^{t} \frac{|g_t|}{|g|}\ E\ (g_t) \tag{22}$$

Moreover, the decision tree uses the Gini index as by default criterion instead of entropy. Because Gini is computationally efficient and takes a shorter period than the entropy. The Gini function can be written in Equation (23) as,

$$Gini\ (u)\ =\ 1 - \sum_{i}^{m} P_i^2 \tag{23}$$

Here, P_i is the probability of the percentage of the positive and negative classes.

B.1.6 Random Forest (RF)

Random Forest (RF) is a powerful algorithm for classifying the data points into different classes. It is constructed of many decision trees, which constitute a RF. Each decision tree determines a class label predictor for each new instance (Arora & Kaur, 2020). The intuition behind the RF is described in some steps as follows:

Step 1: Let's consider a dataset of (C, V) where the set of observations is $\{c_1,\ c_2,\ c_3, \ldots, c_d\}$ and the set of responses is $\{v_1,\ v_2,\ v_3, \ldots, v_d\}$ with bootstrap T datasets of d size. In RF, bootstrapping help for random sampling and replacing data. It will generate another set of data (C_c, V_c) of the size of d from (C, V) for sampling and replacement. For easy to understand here v_i € $(0,1)$ is considered.

Step 2: For $C\ =\ \{1,2,3, \ldots.., c)$ it will train a dataset of (C_c, V_c) using the decision tree.

Step 3: It will take the majority vote from all trees of each decision tree to predict a new observation C^{new}.

Step 4: It will calculate the "out-of-bag error" by calculating the mean prediction error of each decision tree's prediction where the predictions on observation are not included in the bootstrapped sample.

Step 5: By considering "out-of-bag error" it will calculate the feature importance C_j and classify the prominent barriers to adopt BCT is sustainable supply chain management.

B.2 Feature Selection

In feature selection, the main focus is to select the most important features and remove the unnecessary ones from the original feature set (Sharmin et al., 2019). The following section will discuss the BORUTA feature selection algorithm.

B.2.1 BORUTA

BORUTA is a wrapper feature selection algorithm which is developed by (Kursa & Rudnicki, 2010). To minimize the misleading effects of correlations and random variations, BORUTA adds randomness to the system and gathers results from all randomly selected samples (Ebrahimi-Khusfi et al., 2021).

The feature selection technique of the BORUTA algorithm is described in some steps as follows:

Step 1: Let's consider a set of independent features $\{F_1, F_2, F_3, \dots, F_N\}$ for identifying the barriers to adopt BCT in a sustainable supply chain. BORUTA will randomly permute the independent features and creates a set of independent shadow features or attributes $\{ F_1^S, F_2^S, F_3^S, \dots\dots, F_N^S\}$

Step 2: It fits the independent feature and shadow features in the RF by default for calculating the feature importance. A feature is important or not depends on the importance of all shadow features. If the maximum importance of random attributes ($MIRA$) is lower than the original feature, then the feature is considered important. Therefore, if the importance of any original feature $F_N > MIRA$ then the F_N is a significant barrier to adopt BCT.

Step 3: BORUTA will run Step 2 for T times and keep a record of how many times $F_N > MIRA$ this condition occurs.

Step 4: Each run will either select the feature F_N or unselect the feature F_N. So, this procedure follows the binomial distribution. Therefore, the expected number for selecting a feature is in Equation (24),

$$E\ (T)\ =\ 0.5T \tag{24}$$

And the expected standard deviation will be in Equation (25),

$$S\ =\ \sqrt{0.25T} \tag{25}$$

Step 5: The feature will select as an important feature if it's expected number $E\ (T)$ exceeds $0.5T$. The procedure is repeated for a set number of iterations, or until all attributes are rejected or definitively deemed important.

B.3 Performance metrics

In this study, accuracy and f-score are used to measure the performance of ML classifiers using Equation (26) and (27).

$$\text{Accuracy} = \frac{T_p+T_n}{T_p+F_p+F_n+T_n} \tag{26}$$

$$\text{F-score} = \frac{Precision \times Recall}{Precision+Recall} \tag{27}$$

B.4 Grey-DEMATEL

Grey-DEMATEL is a combination of a DEMATEL (Khan et al., 2020) and the Grey Theory that can overcome the limitations of the DEMATEL technique (Bai et al., 2017). Additionally, recent studies analyzed causal relationships between various criteria using the Grey-DEMATEL method (Khan et al., 2022b).

According to our study, Grey-DEMATEL is processed as follows:

Step 1: This step involves developing a fuzzy direct relationship matrix using linguistic scales of five points, as Table 2.

We developed an initial direct relationship matrix for the barriers ($b_i, i = 1,2,3, \ldots n$) to BCT adoption in sustainable supply chain management by D experts using pair-wise comparison and the grey number in Table 2 replaces this matrix's linguistic terms. N number of $V^1, V^2, V^3, \ldots\ V^D$

direct relationship grey matrices are obtained from the D experts. Combining all grey direct-relationship metrics using Equation (28) resulted in an overall grey-relationship matrix.

$$V = \frac{\sum_{i=1}^{D}(V^{D})}{D} \tag{28}$$

Table 2: Linguistic Terms and Their Corresponding Greyscales

Linguistic Terms	**Grey numbers**
No influence(N)	[0,0]
Very low influence (VL)	[0,0.25]
Low influence (L)	[0.25, 0.5]
High influence (H)	[0.5, 0.75]
Very high influence (VH)	[0.75, 1]

Step 2: In this step, the overall grey-relationship matrix converted into normalized direct relation matrix N using the Equation (29) and (30)

$$N = sV \tag{29}$$

$$S = \frac{1}{max_{1\le i\le n}\sum_{j=1}^{n} X\, V_{ij}} \tag{30}$$

Step 3: In this step, the total relationship matrix "T" is determined based on Equation (31) where I represent the identity matrix.

$$T = \sum_{i=1}^{\infty} N^{i} = N\,(I - N)^{-1} \tag{31}$$

Step 4: This step determines the net and causal effects of barriers using Equations (32) to (35):

$$R_i = \sum_{j=1}^{n} t_{ij} \forall_i \tag{32}$$

$$C_j = \sum_{j=1}^{n} t_{ij} \forall_j \tag{33}$$

$$P_i = \{R_i + C_j \mid i = j\} \tag{34}$$

$$E_i = \{R_i - C_j \mid i = j\} \tag{35}$$

Step 5: In this step, the cause-and-effect relationship digraph will be plotted using $(R_i + C_j)$, $(R_i - C_j)$, threshold, and the total relationship matrix (T). $(R_i - C_j)$ will be represented on the vertical axis of digraph, while $(R_i + C_j)$ will be on the horizontal axis. In addition, the positive value of E_i represent the net effect (cause) of the barriers on the system, whereas the negative value represents the net effect on the barriers caused by the system.

Appendix C

<table>
<tr><td colspan="2">Questionnaire on prioritizing and mapping barriers to blockchain technology adoption in sustainable supply chain: a hierarchical cause-and-effect model</td></tr>
<tr><td colspan="2">Part A: Demography of experts</td></tr>
<tr><td>Designation</td><td>○ General Manager
○ Manager
○ Senior Manager
○ Assistant Manager
○ Deputy Manager
○ Other</td></tr>
<tr><td>Education</td><td>○ PhD
○ Master’s
○ Bachelors
○ Post graduate diploma
○ Other</td></tr>
<tr><td>Gender</td><td>○ Male
○ Female
○ Not to prefer</td></tr>
<tr><td>Years of experiences</td><td>○ 2-5 years
○ 6-9 years
○ 10-14 years
○ 15-19 years
○ 20+ years</td></tr>
<tr><td>Age</td><td>○ 22-25 years
○ 26-30 years
○ 31-40 years
○ 41-50 years
○ 51+ years</td></tr>
<tr><td>Working area</td><td>○ Automotive Industry
○ FMCG Industry
○ Furniture Industry
○ Electronics Industry
○ Garments Industry
○ Others</td></tr>
<tr><td colspan="2">Part B: Judgments by experts</td></tr>
</table>

Initially, 26 factors leading to the adoption of blockchain technology in sustainable supply chain management have been identified from the literature and are listed below. Rate the mentioned barriers based on their impact on blockchain adoption in sustainable supply chain management. Here the scaling is done as follows, 1-Poor 2-Not so much 3-Moderate 4-Good 5-Excellent	
Barriers	Ratings
Access	
Immutability	
Immaturity	
Usability	
Security	
Complexity	
Interoperability	
Financial constrains	
Lack of research and development	
External stakeholders' involvement	
Lack of technological tools	
Lack of government policies	
Ethical industry involvement	
Customer's awareness	
Sustainable practices integration	
Risks of cyber-attacks	
Information disclosure policy	

Managerial commitment	
Cultural differences	
Lack of organizational policies	
Knowledge and expertise	
Unwillingness to adopt new systems	
Collaboration and communication	
Negative perception	
Wasted resources	
Lack of rewards and encouragement programs	
Part C: Experts opinion for target variable	
In the event that the barriers to blockchain adoption you have largely focused on were to be removed, how straightforward would it be for sustainable supply chain practitioners to adopt it? Here the scaling is done as follows, 1-Poor 2-Not so much 3-Moderate 4-Good 5-Excellent	○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Appendix D

Table D-1: Result of the BORUTA selection process

No.	Barriers	Mean Imp	Median Imp	Min Imp	Max Imp	NormHits	Decision
1	T1	4.604	4.594	2.103	6.459	0.898	Confirmed
2	T2	2.694	2.783	0.342	5.020	0.404	Tentative
3	T3	14.331	14.237	12.018	16.278	1.00	Confirmed
4	T4	3.189	3.099	1.128	5.812	0.575	Tentative
5	T5	15.633	15.624	13.681	17.134	1.00	Confirmed

6	T6	2.775	2.934	0.054	5.379	0.484	Tentative
7	T7	5.694	5.710	3.331	7.784	0.969	Confirmed
8	E1	13.175	13.214	11.164	15.121	1.00	Confirmed
9	E2	1.521	1.492	-0.933	3.131	0.020	Rejected
10	E3	2.027	2.126	-0.148	3.790	0.060	Rejected
11	E4	8.868	8.977	6.474	10.248	1.00	Confirmed
12	EN1	3.602	3.642	1.240	5.802	0.666	Tentative
13	EN2	1.930	1.932	-0.688	4.143	0.292	Rejected
14	EN3	8.258	8.241	6.476	9.870	1.00	Confirmed
15	EN4	5.226	5.254	2.973	7.560	0.929	Confirmed
16	EN5	3.241	3.304	0.792	5.487	0.616	Tentative
17	O1	3.482	3.410	0.672	5.840	0.686	Confirmed
18	O2	12.084	12.095	10.063	13.366	1.00	Confirmed
19	O3	5.751	5.745	2.223	7.666	1.00	Confirmed
20	O4	5.124	5.131	2.680	7.571	0.919	Confirmed
21	O5	9.00	9.007	6.206	10.970	1.00	Confirmed
22	O6	8.180	8.129	6.913	9.484	0.989	Confirmed
23	O7	2.999	2.802	0.846	5.086	0.565	Tentative
24	S1	6.090	6.071	3.555	8.209	0.969	Confirmed
25	S2	0.776	1.018	-1.146	2.100	0.00	Rejected
26	S3	1.465	1.371	-0.909	4.684	0.030	Rejected

Appendix E

Table E-1: Overall grey direct relationship matrix (z)

	T1		T3		T5		T7		E1		E4		EN3		EN4		O1		O2		O3		O4		O5		O6		S1	
	x	y	x	y	x	y	x	y	x	Y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y
T1	0	0	0.75	1	0.75	1	0.5	0.75	0.75	1	0.75	1	0.75	1	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75	0.75	1	0.5	0.75
T3	0.75	1	0	0	0.75	1	0.5	0.75	0.75	1	0.75	1	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.75	1	0.25	0.5	0.5	0.75	0.5	0.75
T5	0.75	1	0.75	1	0	0	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75
T7	0.75	1	0.75	1	0.75	1	0	0	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75
E1	0.75	1	0.75	1	0.75	1	0.5	0.75	0	0	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75
E4	0.75	1	0.75	1	0.75	1	0.5	0.75	0.75	1	0	0	0.5	0.75	0.75	1	0.75	1	0.5	0.75	0.25	0.5	0.75	1	0.25	0.5	0.5	0.75	0.5	0.75
EN3	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.75	1	0.75	1	0	0	0.5	0.75	0.5	0.75	0.5	0.75	0.25	0.5	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75

EN4	0.75	1	0.75	1	0.75	1	0.5	0.75	0.75	1	0.75	1	0.75	1	0	0	0.75	1	0.5	0.75	0.25	0.5	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75
O1	0.75	1	0.75	1	0.75	1	0.5	0.75	0.75	1	0.75	1	0.75	1	0.5	0.75	0	0	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.75	1	0.75	1
O2	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0	0	0.25	0.5	0.5	0.75	0.25	0.5	0.5	0.75	0.5	0.75
O3	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.75	1	0.75	1	0.5	0.75	0.75	1	0.75	1	0.5	0.75	0	0	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75
O4	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75	0.75	1	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.25	0.5	0	0	0.25	0.5	0.5	0.75	0.5	0.75
O5	0.75	1	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.75	1	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0	0	0.5	0.75	0.5	0.75
O6	0.75	1	0.75	1	0.75	1	0.5	0.75	0.75	1	0.75	1	0.75	1	0.75	1	0.75	1	0.75	1	0.25	0.5	0.5	0.75	0.5	0.75	0	0	0.5	0.75
S1	0.75	1	0.75	1	0.75	1	0.5	0.75	0.5	0.75	0.75	1	0.75	1	0.5	0.75	0.75	1	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0	0

Table E-2: Normalized direct relation matrix (N)

	T1	T3	T5	T7	E1	E4	EN3	EN4	O1	O2	O3	O4	O5	O6	S1
T1	0	0.988	0.988	0.700	0.988	0.988	0.988	0.988	0.988	0.700	0.700	0.988	0.700	0.988	0.700
T3	0.988	0	0.988	0.700	0.988	0.988	0.700	0.988	0.700	0.700	0.700	0.988	0.388	0.700	0.700
T5	0.988	0.988	0	0.988	0.988	0.700	0.700	0.988	0.988	0.700	0.700	0.988	0.700	0.700	0.700
T7	0.988	0.988	0.988	0	0.988	0.700	0.700	0.700	0.700	0.700	0.700	0.988	0.700	0.700	0.700
E1	0.988	0.988	0.988	0.700	0	0.700	0.700	0.988	0.700	0.700	0.700	0.700	0.700	0.700	0.700
E4	0.988	0.988	0.988	0.700	0.988	0	0.700	0.988	0.988	0.700	0.388	0.988	0.388	0.700	0.700
EN3	0.988	0.988	0.700	0.700	0.988	0.988	0	0.700	0.700	0.700	0.388	0.700	0.700	0.700	0.700
EN4	0.988	0.988	0.988	0.700	0.988	0.988	0.988	0	0.988	0.700	0.388	0.700	0.700	0.700	0.700
O1	0.988	0.988	0.988	0.700	0.988	0.988	0.988	0.700	0	0.988	0.700	0.700	0.700	0.988	0.988
O2	0.988	0.988	0.700	0.700	0.988	0.700	0.700	0.700	0.700	0	0.388	0.700	0.388	0.700	0.700
O3	0.988	0.988	0.700	0.700	0.988	0.988	0.700	0.988	0.988	0.700	0	0.700	0.700	0.988	0.700
O4	0.700	0.700	0.988	0.700	0.988	0.700	0.988	0.700	0.700	0.700	0.388	0	0.388	0.700	0.700
O5	0.988	0.988	0.988	0.700	0.700	0.700	0.988	0.700	0.988	0.700	0.700	0.700	0	0.700	0.700
O6	0.988	0.988	0.988	0.700	0.988	0.988	0.988	0.988	0.988	0.988	0.388	0.700	0.700	0	0.700
S1	0.988	0.988	0.988	0.700	0.700	0.988	0.988	0.700	0.988	0.700	0.700	0.700	0.700	0.700	0

	T1	T3	T5	T7	E1	E4	EN3	EN4	O1	O2	O3	O4	O5	O6	S1
T1	0.855	0.929	0.901	0.705	0.918	0.846	0.826	0.834	0.841	0.721	0.571	0.801	0.607	0.757	0.704
T3	0.852	0.778	0.827	0.647	0.843	0.777	0.738	0.767	0.752	0.66	0.525	0.736	0.534	0.675	0.645
T5	0.892	0.892	0.792	0.698	0.882	0.792	0.773	0.801	0.808	0.692	0.55	0.77	0.583	0.708	0.676
T7	0.853	0.853	0.828	0.594	0.843	0.757	0.739	0.747	0.753	0.661	0.527	0.737	0.558	0.677	0.646
E1	0.838	0.838	0.812	0.636	0.753	0.743	0.725	0.753	0.739	0.649	0.517	0.703	0.548	0.664	0.634
E4	0.851	0.851	0.826	0.646	0.842	0.702	0.737	0.765	0.771	0.66	0.502	0.735	0.534	0.675	0.645
EN3	0.815	0.815	0.77	0.618	0.805	0.742	0.651	0.712	0.717	0.631	0.48	0.683	0.532	0.645	0.616

EN4	0.872	0.872	0.846	0.662	0.862	0.795	0.776	0.71	0.79	0.676	0.515	0.732	0.57	0.691	0.661
O1	0.93	0.93	0.9	0.705	0.918	0.846	0.826	0.814	0.767	0.741	0.572	0.78	0.607	0.757	0.724
O2	0.775	0.775	0.732	0.588	0.766	0.687	0.67	0.677	0.682	0.547	0.456	0.65	0.484	0.614	0.587
O3	0.895	0.895	0.848	0.679	0.884	0.816	0.776	0.805	0.811	0.694	0.498	0.751	0.585	0.731	0.678
O4	0.753	0.753	0.75	0.587	0.765	0.685	0.689	0.675	0.68	0.599	0.455	0.595	0.484	0.612	0.586
O5	0.857	0.857	0.83	0.65	0.826	0.761	0.762	0.749	0.776	0.664	0.528	0.719	0.507	0.679	0.649
O6	0.909	0.909	0.881	0.689	0.898	0.827	0.808	0.816	0.822	0.725	0.536	0.763	0.593	0.666	0.688
S1	0.875	0.875	0.848	0.664	0.844	0.798	0.778	0.766	0.793	0.678	0.539	0.735	0.572	0.694	0.61

Table E-3: Total relationship matrix (T) – after threshold

Abbreviations

BCT	Blockchain Technology
Grey-DEMATEL	Grey-Decision-Making Trial and Evaluation Laboratory
KNN	K-Nearest Neighbor
LR	Logistic Regression
MCDM	Multi-Criteria Decision-Making
MIRA	Maximum Importance of Random Attributes
ML	Machine Learning

RF	Random Forest
SCM	Supply Chain Management
SSCM	Sustainable Supply Chain Management
SVM	Support Vector Machine

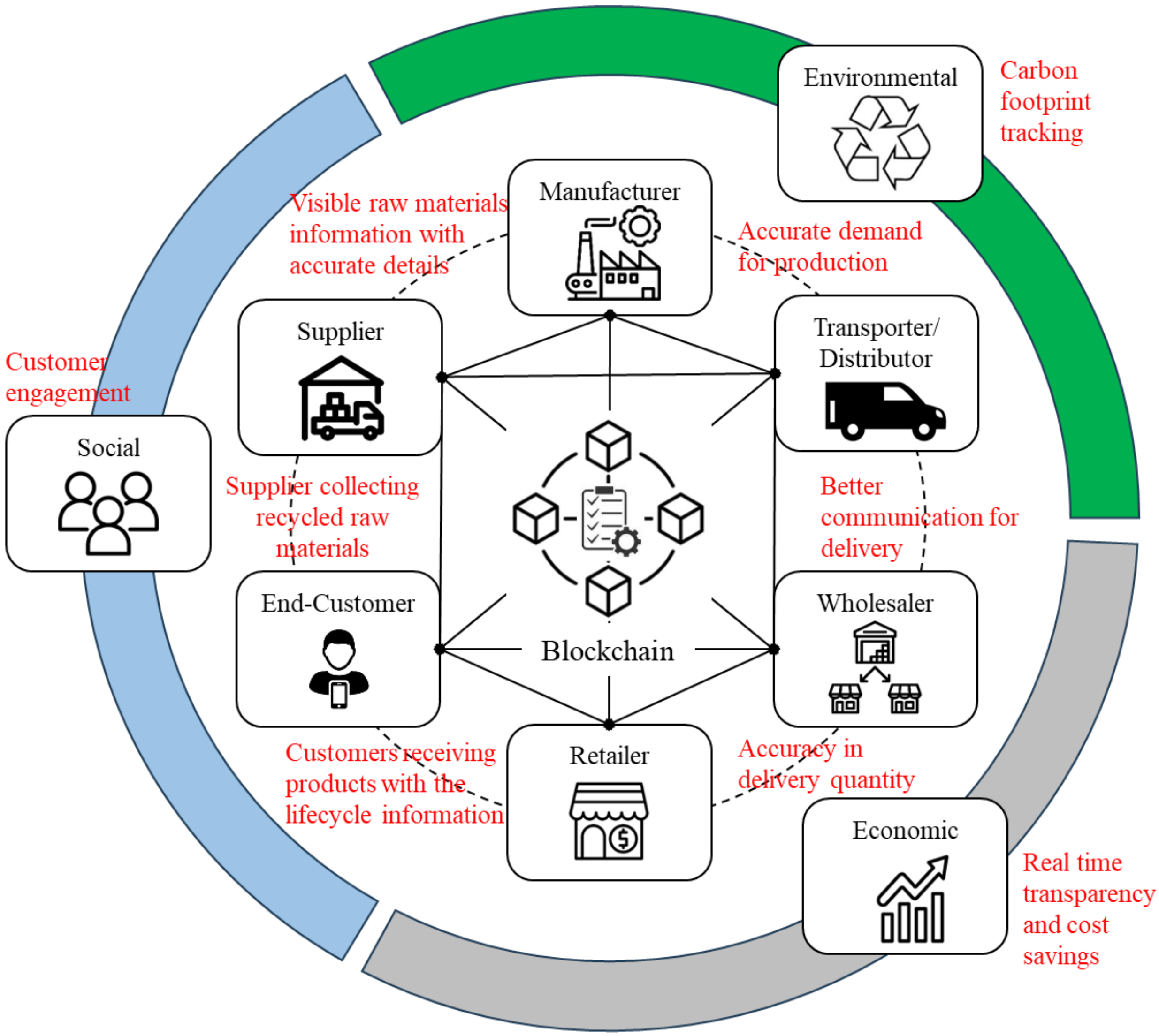

Figure I: BCT-based sustainable supply chain

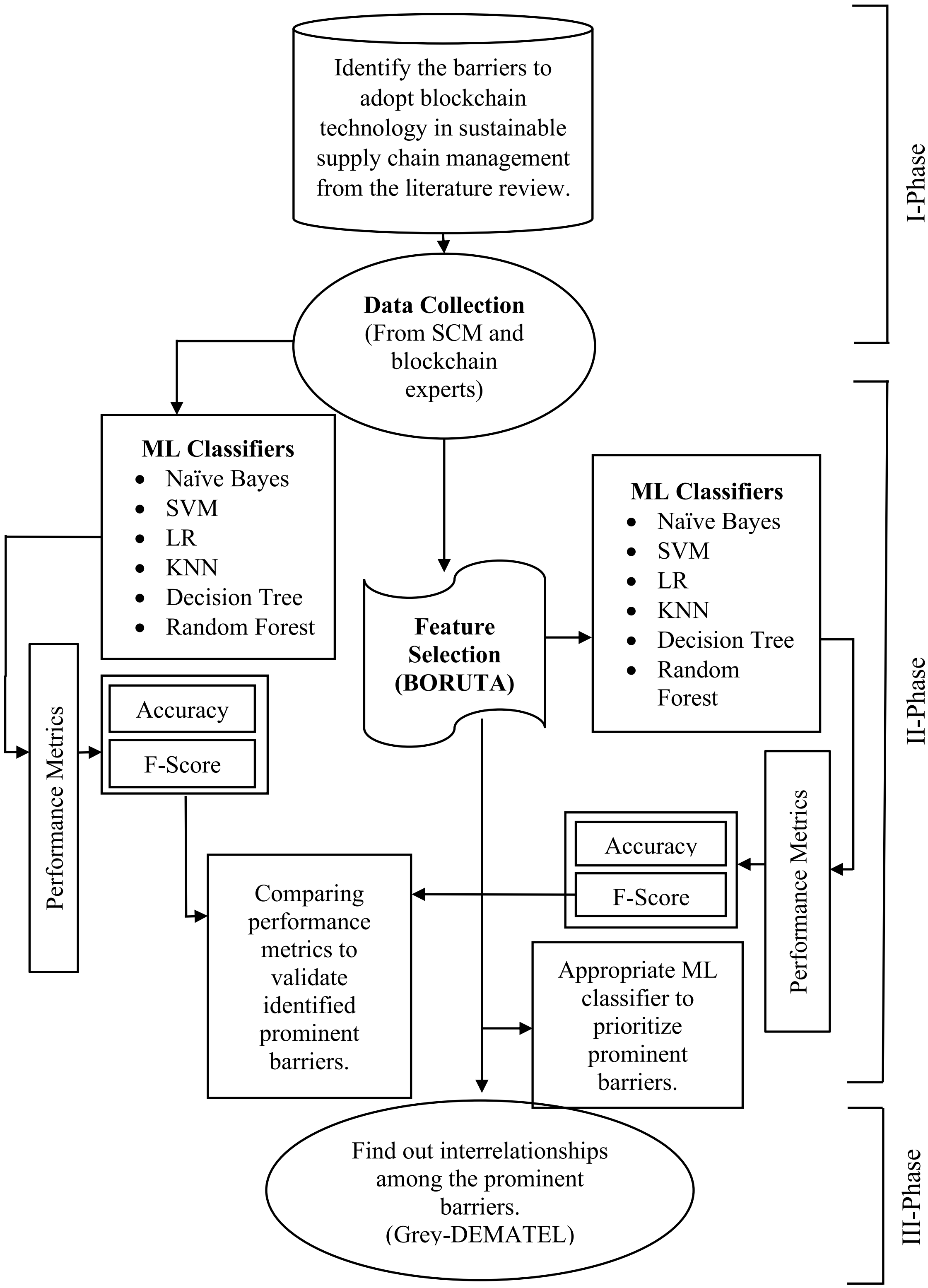

Figure II: The proposed three-phase research methodology framework

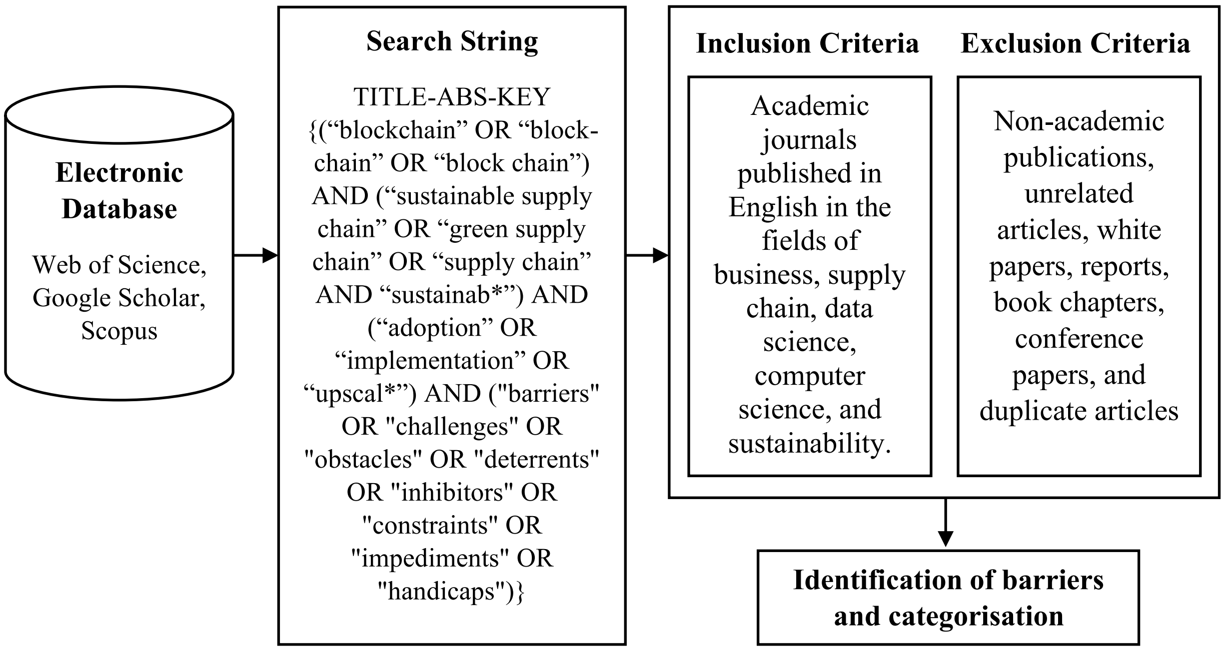

Figure III: The protocol for the identification of the barriers

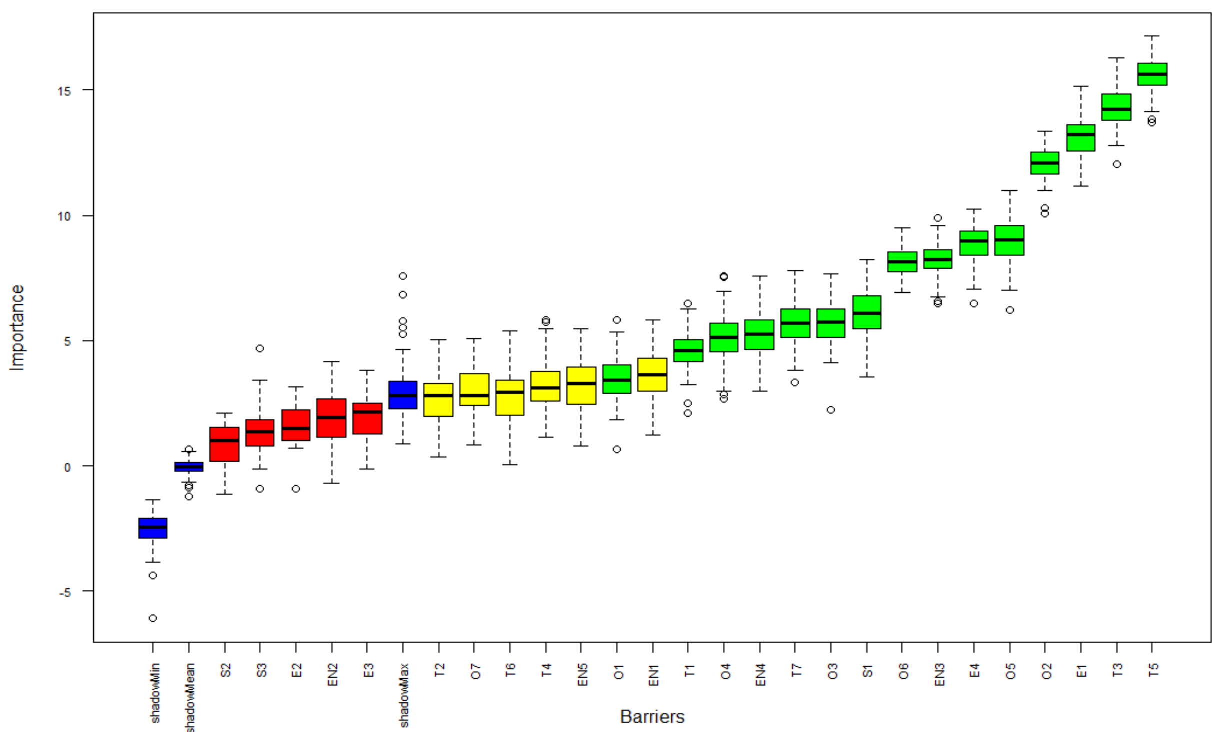

Figure IV: Importance of each barrier using the BORUTA (Feature Selection) algorithm

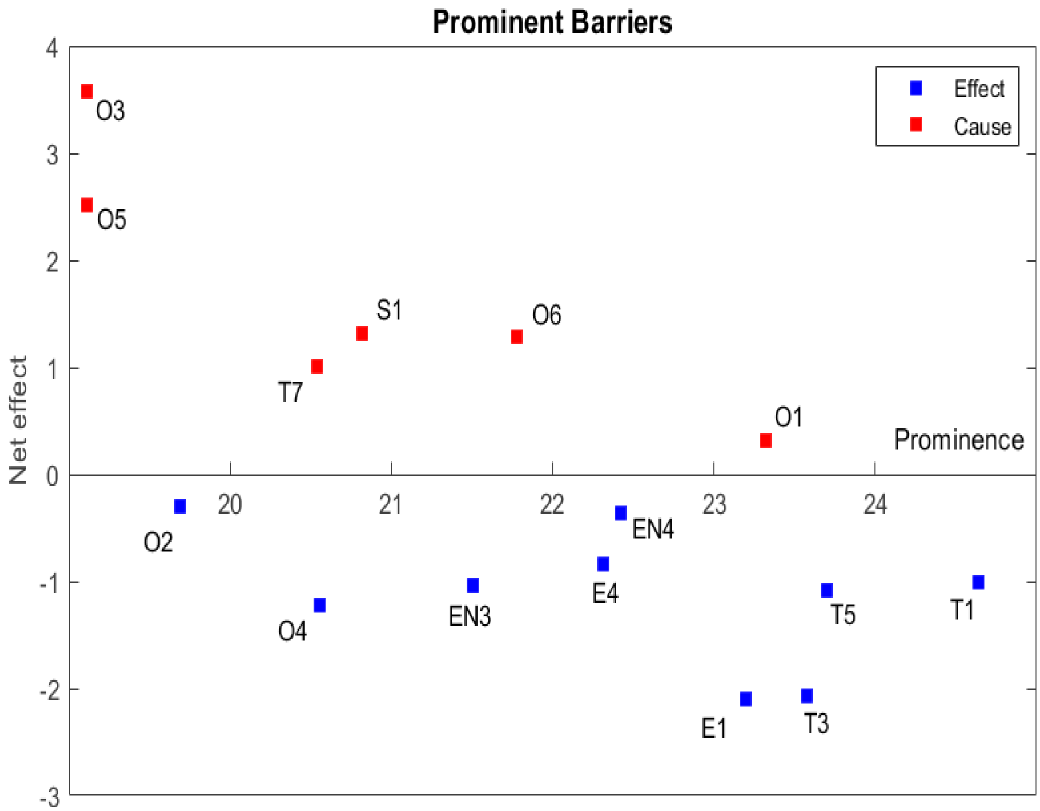

Figure V: Cause-and-effect relationship among the barriers to adopt BCT.

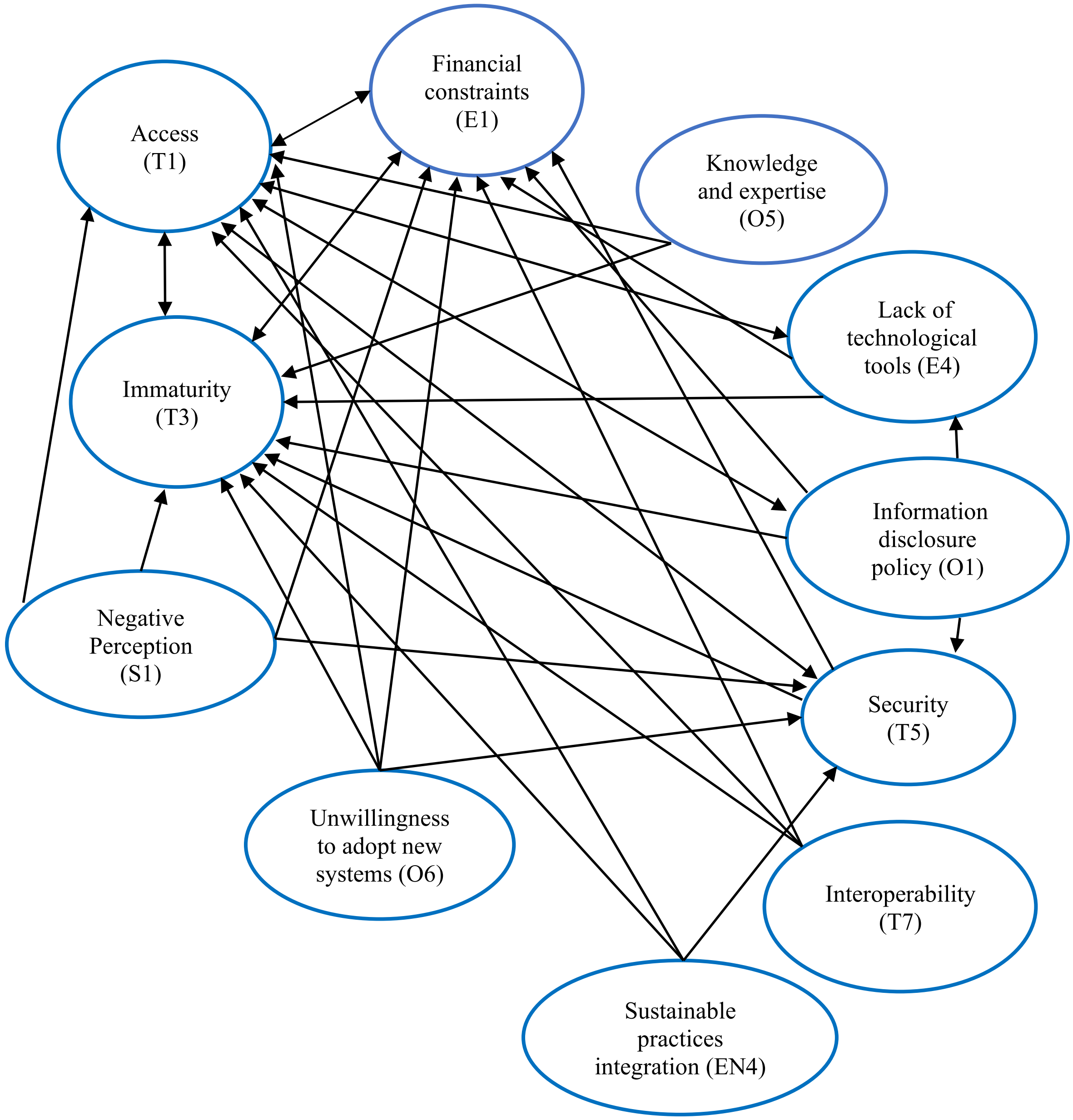

Figure VI: Interrelationships among the prominent barriers according to Grey-DEMATEL

Table I: Details about the experts and case companies

Attributes	n	Total	Attributes	n	Total
Years of Experience			**Designation**		
20+ years	3		General Manager	16	
15-19 years	4		Manager	14	
10-14 years	36		Senior Manager	24	
6-9 years	44		Assistant Manager	52	
2-5 years	123		Deputy Manager	44	
		210	Others	60	210
Education			**Organization**		
PhD	10		Automotive Industry	26	
Masters	100		FMCG Industry	52	
Bachelors	80		Electronics Industry	34	
Post graduate diploma	20		Furniture Industry	34	
			Garments Industry	46	
		210	Others	16	210
Age			**Gender**		
51 + Years	2		Male	160	
41-50 Years	8		Female	50	
31-40 Years	62		Not mentioned		
26-30 Years	88				
22-25 Years	50	210			210

Table II: Results of ML Classifiers before applying Feature Selection

ML Classifiers	**Accuracy**	**F-Score**
Naïve Bayes	78.57 %	79.03 %
Logistic Regression	71.42 %	72.29 %
Support Vector Machine	78.57 %	75.39 %
K-Nearest Neighbor	83.33 %	79.18 %
Decision Tree	80.95 %	80.95 %
Random Forest	88.09 %	86.98 %

Table III: Results of ML Classifiers after applying Feature Selection

ML Classifiers	**Accuracy**	**F-Score**
Naïve Bayes	88.09 %	88.35 %
Logistic Regression	88.09 %	88.39 %
Support Vector Machine	85.71 %	84.34 %
K-Nearest Neighbor	85.71 %	83.76 %
Decision Tree	88.09 %	86.98 %

Random Forest	90.47 %	89.17 %

Table IV: Importance of the prominent barriers according to RF

Barriers	% of Importance	Rank
Financial constraints (E1)	10.63	1
Immaturity (T3)	9.94	2
Security (T5)	9.53	3
Knowledge and expertise (O5)	8.67	4
Cultural differences (O3)	7.26	5
Lack of technological tools (E4)	7.08	6
Managerial commitment (O2)	6.55	7
Negative perception (S1)	6.42	8
Lack of organizational policies (O4)	5.81	9
Interoperability (T7)	5.76	10
Access (T1)	5.32	11
Information disclosure policy (O1)	4.84	12
Customers' awareness (EN3)	4.74	13
Sustainable practices integration (EN4)	4.42	14
Unwillingness to adopt new systems (O6)	3.01	15

Table V: Direct relationship matrix (average)

	T1	T3	T5	T7	E1	E4	EN3	EN4	O1	O2	O3	O4	O5	O6	S1
T1	0	4	4	3	4	4	4	4	4	3	3	4	3	4	3
T3	4	0	4	3	4	4	3	4	3	3	3	4	2	3	3
T5	4	4	0	4	4	3	3	4	4	3	3	4	3	3	3
T7	4	4	4	0	4	3	3	3	3	3	3	4	3	3	3
E1	4	4	4	3	0	3	3	4	3	3	3	3	3	3	3
E4	4	4	4	3	4	0	3	4	4	3	2	4	2	3	3
EN3	4	4	3	3	4	4	0	3	3	3	2	3	3	3	3
EN4	4	4	4	3	4	4	4	0	4	3	2	3	3	3	3
O1	4	4	4	3	4	4	4	3	0	4	3	3	3	4	4
O2	4	4	3	3	4	3	3	3	3	0	2	3	2	3	3
O3	4	4	3	3	4	4	3	4	4	3	0	3	3	4	3
O4	3	3	4	3	4	3	4	3	3	3	2	0	2	3	3
O5	4	4	4	3	3	3	4	3	4	3	3	3	0	3	3
O6	4	4	4	3	4	4	4	4	4	4	2	3	3	0	3
S1	4	4	4	3	3	4	4	3	4	3	3	3	3	3	0

Table VI: Degree of prominence and Degree of effect

Mean	0.725
S.D.	0.111
Threshold	0.836

	Ri+Ci	Ri-Ci
T1	24.64	-1.006
T3	23.58	-2.068
T5	23.7	-1.083
T7	20.54	1.004
E1	23.2	-2.099
E4	22.32	-0.832
EN3	21.51	-1.042
EN4	22.42	-0.362
O1	23.32	0.317
O2	19.69	-0.305
O3	19.12	3.577
O4	20.56	-1.22
O5	19.11	2.515
O6	21.77	1.283
S1	20.82	1.322