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Benchmarking blockchain adoption enablers in automotive supply chains: a hybrid machine learning–TISM–MICMAC framework

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Abstract

Purpose – Blockchain technology is increasingly viewed as a key enabler of transparency, traceability and resilience in automotive supply chains; however, adoption priorities differ markedly between electric vehicle (EV) and traditional vehicle (TV) manufacturers. This study aims to benchmark and compare blockchain adoption enablers across EV and TV supply chains and to develop a structured, sector-specific decision framework to support managerial and strategic adoption decisions.

Design/methodology/approach – The study proposes a hybrid multi-method framework integrating supervised machine learning techniques (random forest, permutation importance and BORUTA) with total interpretive structural modeling and Matrice d'Impacts Croisés Multiplication Appliquée à un Classement analysis. Expert evaluations from 100 professionals across the automotive and digital transformation domains were analyzed to shortlist and structurally model high-impact blockchain adoption enablers.

Findings – From an initial set of 30 enablers, 12 critical enablers were identified and hierarchically structured. Results indicate that EV manufacturers prioritize sustainability, traceability and innovation, whereas TV manufacturers emphasize cost efficiency, cybersecurity and regulatory compliance. Robust cybersecurity infrastructure, regulatory governance and risk management emerge as foundational enablers across both sectors.

Research limitations/implications – The study relies on expert judgment within the automotive sector, which may limit generalizability to other industries. Future research could extend the framework by incorporating Internet of Things and artificial intelligence enablers and validating the model across additional industrial contexts.

Practical implications – The proposed framework provides managers and policymakers with a structured roadmap for prioritizing blockchain investments, aligning adoption strategies with sector-specific objectives and targeting high-leverage enablers to accelerate digital transformation in automotive supply chains.

Social implications – By supporting transparent, traceable and secure supply chain operations, blockchain adoption can enhance sustainability performance, regulatory accountability and stakeholder trust across automotive ecosystems.

Originality/value – This study offers a novel integration of machine learning-based feature selection with interpretive structural modeling to benchmark blockchain adoption enablers across EV and TV manufacturers, delivering a decision-oriented, sector-comparative modeling framework for digital supply chain transformation.

Keywords Blockchain, Automotive industry, Enablers, Machine learning, ISM-MICMAC, BORUTO, PESTLE

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1. Introduction

Automotive supply chains have become increasingly complex and geographically dispersed, creating persistent challenges related to transparency, responsiveness and trust among supply chain partners (Wissuwa and Durach, 2021). The shift toward Industry 4.0, characterized by digital integration, automation and real-time data exchange, has intensified the need for secure and decentralized data management solutions capable of addressing these operational inefficiencies (Bai *et al.*, 2020; Angelopoulos *et al.*, 2023; Stark *et al.*, 2023). In this context, blockchain technology (BCT) has emerged as a promising approach for enhancing traceability, information sharing and operational security through its distributed and tamper-resistant ledger architecture (McBee and Wilcox, 2016; Zhang *et al.*, 2021; Al Shamsi *et al.* 2023).

Despite these developments, large-scale adoption of blockchain within automotive supply chains remains limited. Existing studies often focus on conceptual discussions or isolated pilot implementations, leaving a gap in empirical understanding of the specific enablers driving adoption in this sector (Bader *et al.*, 2021; Chen *et al.*, 2020). Moreover, automotive ecosystems are undergoing structural transformation as electric vehicle (EV) manufacturers prioritize sustainability and innovation, while traditional vehicle (TV) manufacturers emphasize efficiency, cybersecurity and regulatory compliance. These contrasting priorities suggest that blockchain adoption cannot be understood through a one-size-fits-all perspective, highlighting the need for a sector-sensitive analytical approach.

To address this gap, this study investigates the key enablers of blockchain adoption within automotive supply chains and examines their structural interrelationships. The research uses a hybrid methodological framework that integrates machine learning (ML)-based prioritization with total interpretive structural modeling (TISM) and Matrice d’Impacts Croisés Multiplication Appliquée à un Classement (MICMAC) analysis. Enablers are categorized using the PESTLE framework, while theoretical insights are informed by the technology–organization–environment (TOE) framework, institutional theory and the resource-based view (RBV), enabling a multi-level understanding of technological, organizational and environmental drivers shaping blockchain adoption (Appendix Section 1).

This makes blockchain an important advancement toward incremental supply chain resilience and responsiveness. Resilience is a measure of a supply chain’s ability to predict and recover from a serious disruption, and responsiveness is its ability to quickly adapt to market demands (Christopher and Holweg, 2011). Blockchain enhances both through real-time visibility into supply chain activities, which, in turn, enables quicker decision-making and partnership collaboration with supply chain partners (Chen *et al.*, 2020; Bader *et al.*, 2021). An instance is the Jaguar Land Rover blockchain initiative, in which drivers are rewarded for sharing vehicle information, thus creating incentives for customer involvement with a promising greater collection of real-time data, which much contributes to heightened supply chain responsiveness and flexibility (Brown *et al.*, 2010). Such features position blockchain as a game-changing solution to fostering agile, secure and efficient supply chains capable of withstanding the challenges of an increasingly dynamic and regulated marketplace.

While blockchain holds great promise in terms of innovation in the automotive sector, there are several impediments to the actualization of widespread adoption in automotive supply chains. Regulatory and compliance woes, such as privacy issues or cybersecurity conditions, also need to be addressed to make heavy usage of blockchain practical. A systematic analysis of the drivers and challenges in blockchain adoption specific to automotive supply chains is essential to uncover effective implementation strategies and maximize its value for stakeholders (Mougayar, 2016; Tapscott and Tapscott, 2016).

Therefore, the present study addresses this gap of knowledge from two aspects:

1. identification and analyses of key enablers in the adoption of blockchain for the automotive sector; and
2. how to enhance transparency, traceability and efficiency thereof.

Given the unique complexities of automotive supply chains, this study explores how BCT can address previously identified challenges and derives action-oriented recommendations for its strategic implementation. To guide the investigation, two research questions are proposed:

RQ1. What are the most influential enablers of blockchain adoption in the automotive supply chain, as identified through a data-driven machine learning approach?

RQ2. How are the interrelationships and hierarchical structure of blockchain adoption enablers organized within the automotive supply chain, and how can TISM and MICMAC analysis reveal their driving and dependent roles?

The research uses the PESTLE model for categorizing the enablers of BCT adoption, covering political, economic, social, technological, legal and environmental factors, respectively. The theoretical foundation of this research is based on the TOE framework, along with institutional theory and resource-based theory. The TOE framework is a holistic approach for understanding the adoption of technology by considering various technological, organizational and environmental factors (Clohessy and Acton, 2019; Beltrami *et al.*, 2021). For example, in the automotive supply chain, the importance of cybersecurity and automation technologies as an enabler of blockchain adoption is a technological factor, whereas organizational factors include those of governance structures and practices, and environmental factors include regulatory compliance and sustainability. Furthermore, institutional theory helps in understanding the different approaches of EV manufacturers and TV manufacturers in responding to institutional pressures from various regulatory bodies, sustainability and legitimacy, thereby affecting the relative importance of various blockchain adoption enablers. At the same time, resource-based theory explains that capabilities in cybersecurity, organizational structures and practices, and automation technologies are essential determinants for achieving a competitive advantage in adopting BCT. Rather than replacing the existing framework of PESTLE analysis, these theories provide additional insights into the justifications for the hierarchical relationships that are considered in this research, as depicted in the hybrid ML and TISM–MICMAC methodology.

Among the key enabling factors are the need for standardization, interoperability and data protection for the integration of BCT. Standardization helps in the development of level playing fields for accessing information. Interoperability helps in the efficient exchange of data with different platforms and stakeholders (Saberi *et al.*, 2019). Data protection through encryption helps in the protection of intellectual property rights as well as confidential information in the supply chain (Crosby *et al.*, 2016). Further, the integration of smart contracts helps in the automation of transactions with reduced need for intervention. There are also governance factors that address the need for privacy, regulatory compliance and ethical use of data (Bader *et al.*, 2021). Yet, for the application of blockchain in automotive supply chains to be effective, it must be framed within principles of responsible innovation that account for ethical deployment, anticipate risks and deal with unintended consequences (Francisco and Swanson, 2018). While blockchain brings immense advantage in the form of transparency and sustainability, challenges such as data privacy, regulatory ambiguity and power imbalances among the stakeholders must be addressed (Chauhan and Rani, 2024). Resilient design of the blockchain ecosystem will have to take into account meticulous planning involving decentralization, confidentiality, ethical governance and regulatory savvy to enable secure and sustainable supply chains in electric and traditional automotive production (Tseng *et al.*, 2018).

2. Literature review

The market shares for automotive products exist within intricate links of supply chains characterized by webs of closely knit suppliers, high quality standards and heavy operational costs. In their quest to meet the expectations of consumers and regulatory bodies, it becomes a must for manufacturers to have transparency and accountability within all stages of production and distribution. This intricate network, therefore, calls for strong solutions to solve challenges posed by geographical distancing, dependency on multiple supply tiers and the need for real-time information and data exchange (Christopher and Holweg, 2011; Gurtu and Johny, 2019). On account of the global nature of their operations, maintaining consistent quality across the various tiers of suppliers has remained a constant quality-related challenge for all automotive companies (Steven *et al.*, 2014; Franke *et al.*, 2024). Confronted with these challenges exists a rising interest in revolutionizing supply chain processes via BCT in the automotive sector.

At first, when Bitcoin and other cryptocurrencies were being set up, various technical solutions were pointed to as groundwork to sustain these ideas or as it has been called, the "Block Chain" (Nakamoto, 2008). It must be emphasized that BCT has grown over these years, graduating far away from the initial designation. The decentralized-immutable property provides unique capabilities that are suitable for some of the automotive industry's needs. Addressing major supplier chain issues related to counterfeit parts, delayed deliveries and lack of multi-tier supplier transparency calls for blockchain in providing a secure, unalterable ledger for tracking goods and information (Treiblmaier, 2018). Within the automotive industry, where the authenticity and origin of auto parts call for paramount attention, blockchain builds a rakish solution for manufacturers striving to interpret and develop resilient and reliable networks.

The literature on blockchain adoption across various industrial contexts highlights the advantages and challenges it brings about (de Treville *et al.*, 2023). In an empirical investigation involving multiple sectors, including automotive, Queiroz and Wamba (2019) highlight the considerable advantages blockchain offers in terms of real-time visibility and secure data sharing. They also identify a number of barriers such as technological complexity, absence of industry protocols and associated infrastructure development costs. Despite the challenges faced, the automotive industry is particularly positioned to use the technology that might bring significant improvement in accurate tracking and effective data management through extensive supply networks.

Blockchain is selective in its applicability to not only the automotive sector but also food supply chains. Behnke and Janssen (2020) showcase blockchain as an affordance for product traceability. While their focus is in the space of food safety, the lessons they underscore are also relevant to the automotive industry, where ensuring part authenticity and tracking components through supply chains is crucial. Counterfeit parts arising in the automotive industry pose dire threats to safety and branding, while a transparent ledger provided through blockchain allows for a powerful antidote to the threats by providing an unbroken chain of custody from the supplier to the manufacturer to the consumer.

An additional area where cars in the production line see the potential benefits of blockchain is in the domain of environmental protection and sustainability. Saberi *et al.* (2019) propose blockchain enables sustainable supply chain monitoring through the promises of transparency and immutable record-keeping of environmental impact. In fact, this character of technology is especially pertinent at a time when automotive firms are urged to practice eco-friendliness and satisfy anomalous regulatory demands from their governments about emission control and sustainable sourcing. The ramified ability of blockchain to statistically support sustainable practices, material sourcing and environmental data logging would generate a win–win situation to manufacturers about their footing in sustainable counteracting consumer demand with responsible manufacturing standards.

Despite the obvious advantages that can be derived from the use of BCT in the automotive industry, there are a number of challenges that hinder its adoption. A comprehensive analysis by Sharma *et al.* (2020) highlights some of the main challenges affecting the adoption of BCT in different industries. Some of the main challenges include issues of scalability, regulations and interoperability. In the context of the automotive industry, the sheer number of transactions and the need for interoperability with existing systems make the situation even more challenging. Unless the technical challenges are addressed and industry standards set, it is unlikely that the potential offered by this technology will be realized.

Other issues attracting the attention of Yuan and Wang (2018) in the discussion of blockchain are its relevance within intelligent transportation systems, which are closely associated with the automotive field. They further expound that blockchain can contribute to the enhancement of data security of vehicle-to-vehicle or vehicle-to-infrastructure communication, which are key in the development of autonomous and connected cars. The BCT for securing data exchange in the networks of connected cars will become increasingly indispensable as automobile manufacturers provide increased attention to connected car technologies, helping support the safe and efficient workings of advanced transportation systems.

While the studies listed in Table 1 used the MCDM techniques as well as other related analytical techniques to investigate the factors that affect the adoption of BCT, the studies were more method-focused with little emphasis on the theoretical foundations that link environmental pressures, organizational capabilities and technological readiness. Using the TOE model as well as the theoretical foundations of the institutional model, the present study contributes to the extant research in the following manner: it combines data-driven feature selection with interpretive structural modeling (ISM) in a manner that provides a theoretically motivated account for the observed differences in the adoption priorities of EV manufacturers as opposed to TV manufacturers under varying environmental conditions.

Among the most dominant themes in the blockchain research paradigm is the role of transparency as well as traceability in the overall value chain. Several studies have highlighted the role of blockchain in ensuring the real-time tracing of products from the point of origin to the destination. Crosby *et al.* (2016) argue that in industries such as the automotive sector, where the quality of products is paramount, blockchain can serve as a game-changing tool. Furthermore, Saberi *et al.* (2019) argue that blockchain can improve traceability while at the same time reducing the risks associated with counterfeit components, while ensuring the integrity of the overall value chain.

Based on current research, this paper fills the critical gap observed in the existing literature by assessing factors driving the adoption of blockchain technologies by traditional and EV manufacturers in the automotive industry. Though studies like Upadhyay *et al.* (2021) and Queiroz and Wamba (2019) established the role of blockchain

Table 1. Summary of studies using MCDM techniques for blockchain adoption

Reference	Objective	Country	Methodology
Fernandez-Vazquez *et al.* (2022)	Evaluate blockchain adoption in sustainable supply chain management	Spain	AHP
Queiroz and Wamba (2019)	Explore blockchain adoption drivers across industries, including automotive	USA	DEMATEL
Saberi *et al.* (2019)	Analyze blockchain's role in enabling sustainable supply chains in automotive	Global	TOPSIS
Fraga-Lamas and Fernández-Caramés (2019)	Examine blockchain's potential for improving cybersecurity in automotive operations	Spain	Fuzzy AHP
Alladi *et al.* (2019)	Assess blockchain adoption for securing connected vehicles and IoT ecosystems	Global	MCDM framework, analytical network process (ANP)
Dutta *et al.* (2020)	Investigate blockchain's role in improving supply chain transparency and traceability in automotive	India	VIKOR and TOPSIS
Yuan and Wang (2018)	Evaluate blockchain's security benefits for vehicle-to-vehicle and vehicle-to-infrastructure systems	China	PROMETHEE II

Source(s): Author's own work

in increasing efficiency in supply chains, reducing counterfeit levels and responding to sustainable challenges, they tended to be oriented toward more general frameworks rather than specific priorities in sectors. While several studies have applied multi-criteria decision making techniques to evaluate blockchain enablers, many rely exclusively on subjective expert judgment for assigning weights. This introduces potential bias in the ranking process. To address this gap, the current study initiates with a ML-based feature selection stage, using techniques like random forest (RF) and permutation importance. This data-driven phase ensures that the most influential enablers are prioritized for subsequent interpretive modeling using TISM and MICMAC.

3. Research methodology

To accomplish the research objectives and systematically identify, prioritize and structurally model the key enablers for BCT adoption in the automotive supply chain, a three-phase hybrid methodological framework was adopted, as depicted in Figure 1. This methodology integrates expert opinion, supervised ML and ISM, offering both data-driven rigor and contextual interpretability.

The three sequential phases are outlined below.

3.1 *Identification and categorization of enablers*

The study was initiated with a structured literature review, which was conducted through Scopus, Web of Science, IEEE Xplore and Google Scholar using combinations of the

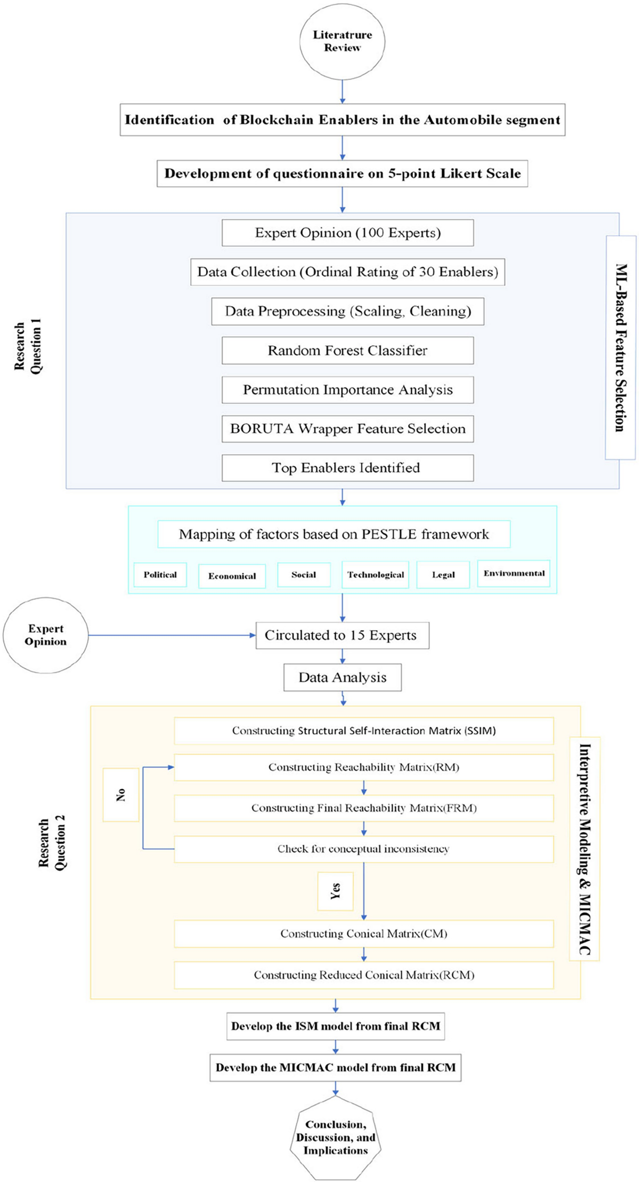


Figure 1. Research methodology conceptual model
Source: Author’s own work

following keywords: “blockchain adoption enablers,” “automotive supply chain” and “Industry 4.0.” The search resulted in an initial set of 50 enablers. However, after the application of the set of relevance-based criteria and the elimination of duplicates, the number was further narrowed down to 30 key enablers. The results were further refined through the opinions and inputs provided by five domain experts from the industry and academia.

In the second stage, the study used the use of supervised ML for the prioritization of the enablers. Input was collected from 100 professionals, including original equipment manufacturer (OEM), EV start-up, Tier-1 supplier and blockchain/ Information technology (IT) consulting firm professionals. The panel included participants with varying roles, such as general managers and digital transformation leads and varying educational backgrounds, such as 6% with a PhD, 56% with a master’s, 30% with a bachelor’s and 8% with a postgraduate diploma. The participants also included people with varying age groups and genders, with 74% being male and 26% female. The results were used to train the RF classifier and apply BORUTA-based feature selection, which resulted in the selection of 12 enablers from the set of 30.

In the third stage, the enablers selected in the second stage were further evaluated using TISM and MICMAC analysis through a panel of 20 senior industry experts from global corporations such as Ford, Tesla, Tata Motors, Škoda, BYD Auto and NIO. The participants, with an average experience level of more than 14 years, included Directors of Digital Strategy, Senior Blockchain Managers, Product Managers and environmental, social, and governance (ESG) Leads. The results were used to generate the hierarchical structure and contextual influence map of the major blockchain adoption enablers.

3.2 Machine learning-based enabler prioritization

In Phase 2, supervised ML techniques were applied to objectively prioritize the most influential enablers. This data-driven step helps minimize bias and validate expert-identified factors using quantitative evidence. The supervised learning process uses the binary adoption likelihood feature constructed through expert ratings as a target feature. Evaluation of the model is carried out through accuracy, precision, recall and F1-score. More details on the configuration of the model can be found in Section 4.2.

The selection of the RF algorithm, permutation importance and BORUTA is driven by the need to balance robustness with feature selection interpretability in the expert-rated data set. RF is used to handle issues such as nonlinearity, multicollinearity and issues arising due to small yet highly feature-rich data sets that characterize expert ratings. Permutation importance is used to verify feature selection through a model-agnostic approach. BORUTA is used to rigorously verify feature selection through statistical means by comparing the original data set with a randomized set of attributes. Overall, this selection provides a clear feature selection approach that is grounded in data-driven verification, complementing the PESTLE categorization approach used in this research.

3.2.1 Random forest classifier. RF is a widely used ensemble method that constructs multiple decision trees to classify data and estimate feature importance. The importance of a feature f_i is derived from the mean decrease in Gini impurity across all trees:

$$Importance(f_i) = \frac{1}{T}\sum_{t=1}^{T} \Delta I_{f_i}^{(t)} \tag{1}$$

where:

- T = number of trees; and
- $\Delta I_{f_i}^{(t)}$ = impurity decrease due to feature f_i in tree t.

3.2.2 Permutation importance. To verify the robustness of RF results, permutation importance was used. It measures the change in model accuracy when feature values are randomly shuffled:

$$PI(f_i) = \frac{1}{N}\sum_{j=1}^{N}\left(Accuracy_{Original} - Accuracy_{shuffled,j}\right) \tag{2}$$

3.2.3 BORUTA algorithm. Next, the BORUTA wrapper algorithm was used to confirm important features by comparing them to shadow variables (randomized copies). BORUTA computes a *Z*-score for each feature:

$$Z(f_i) = \frac{\mu f_i - \mu_{shadow}}{\sigma_{shadow}} \tag{3}$$

Features significantly better than the best shadow feature are marked as "confirmed," while others are either "tentative" or "rejected" (Kursa and Rudnicki, 2010). Only the 12 confirmed enablers were retained for the final phase. This ML-driven feature selection adds an objective filter before qualitative structuring, a step that enhances robustness (Kabir *et al.*, 2020).

From the conceptual standpoint, the ML phase is theoretically conceived as an analytic mechanism incorporated in the theory that implements the PESTLE contextual categorization using statistical techniques to determine the set of most explanatorily relevant enablers rather than as a separate preliminary step. The process combines data-driven learning with theoretically driven constructs to ensure that the feature selection process is driven by meaningful technological, organizational, environmental and institutional dynamics rather than merely data-driven algorithms. The selected set of valid enablers serves as the foundation for the subsequent TISM–MICMAC phase that reverses the focus from predictive relevance to interpretive relevance by modeling the hierarchical structure, causal linkages and driving dependence in the adoption system. The conceptual continuity between the two phases is theoretically grounded in the complementarity of the TOE framework, institutional theory and the RBV. The TOE framework provides the overall multi-level structure that links the levels of technological readiness, organizational capabilities and environmental influences. Institutional theory grounds the regulatory and legitimacy-driven influences on the adoption process. The RBV provides the theoretical foundation for the role of strategic resources in the positioning of the enablers in the overall hierarchical structure. In this manner, the ML component establishes its empirical salience as well as its theoretical alignment with the overall framework. The TISM–MICMAC phase extends the overall process to ISM that facilitates the transition from variable-driven importance to systemic understanding. Accordingly, the hybrid framework can be conceptualized as a unified theory-driven methodological structure in which the quantitative feature selection process and the ISM process represent epistemologically complementary components of a unified analytical logic rather than as sequentially separate methodological steps. The stability of the RF model structure was confirmed by the performance evaluations reported in Section 4.2.

3.3 Interpretive structural modeling and MICMAC

In Phase 3, the 12 prioritized enablers were subjected to TISM and MICMAC analysis. TISM builds a multi-level hierarchy based on contextual relationships among enablers.

Using expert input, a structural self-interaction matrix (SSIM) was developed and transformed into a final reachability matrix:

$$R^{+} = R \vee (R \cdot R)$$

where:

- R = binary reachability matrix;
- $\vee$ = logical OR; and
- $\cdot$ = Boolean matrix multiplication.

Each enabler was evaluated through reachability, antecedent and intersection sets to derive its level.

Next, MICMAC analysis was performed to classify enablers into four clusters – drivers, linkage, dependent and autonomous – based on driving and dependence power:

$$Driving\ Power = \sum_{j=1}^{n} r_{ij} \tag{4}$$

$$Dependence\ Power = \sum_{i=1}^{n} r_{ij} \tag{5}$$

This interpretive stage places the structural impact of each enabler in context, thus providing the basis for the development of a strategic roadmap for the adoption of blockchain in the automotive industry's supply chain. To ensure structural validity as well as analytical rigor in the study's approach, the inclusion of a layer for ML-based feature selection is incorporated in the study. RF is used for the analysis due to its ability to accommodate nonlinear relationships as well as the provision for embedded importance scores. Permutation importance is used to ensure the study's robustness as an approach to assess the relevance of features in a manner that is independent of the model used. The inclusion of the BORUTA approach further adds robustness to the study through the statistical testing of each enabler against randomly generated "shadow" features. By including the ML-based approach in addition to the TISM and MICMAC methods, the study is able to provide a framework that is in line with contemporary calls for increased methodological rigor in the study of technology adoption (Godet, 1986; Jain and Raj, 2016).

4. Result and conclusions

This section highlights the significant findings emerging from the integrated three-phase methodology framework that includes literature identification, ML-based prioritization and interpretive modeling through TISM and MICMAC analysis. Starting with the initial set of 30 enablers, a meticulous feature selection process through RF, permutation importance and BORUTA algorithm has been used to reduce the set to a more impactful set of 12 enablers. Subsequent TISM has been used to understand the hierarchical relationships between the enablers. Further, the enablers have been grouped through MICMAC analysis. This methodology has provided a comprehensive understanding of how a set of enablers drives the adoption of BCT in the automotive supply chain. The subsequent subsections describe the ML results, the hierarchy developed through TISM and the classification through MICMAC analysis, along with the implications.

4.1 Expert profiling and data collection for machine learning-based prioritization of blockchain enablers

For the ML phase of the study, expert evaluations were collected from a total of 100 professionals with direct experience in automotive supply chain management, blockchain implementation and digital transformation. These experts represented a wide spectrum of designations, experience levels and subindustries within both electric and TV manufacturing (Table 2). Participants were asked to rate 30 enablers of blockchain adoption on a five-point Likert scale (ranging from 1 = "Not Important" to 5 = "Extremely Important") (see Appendix Section B1, B2 and B3 for more details).

These enablers were derived from prior literature and validated by a pilot group. The goal of this phase was to generate an ordinal data set suitable for ML-based feature importance extraction and prioritization.

4.2 Enabler identification and finalization for blockchain adoption in the automotive supply chain

In the first stage of this research, the initial set of 30 potential enablers for blockchain adoption was identified through a thorough literature review and was further validated with the help of expert feedback. The panel of experts comprised 100 professionals with backgrounds in conventional and EV manufacturing industries, IT consulting services and tier-1 automotive suppliers. The panel of experts rated the identified enablers on a five-point Likert scale; hence, the input data for the ML stage was developed.

In the second stage of the research, all 30 enablers were considered independent variables and fed as input to ML classifier algorithms. The dependent variable or the target was defined as a binary variable representing the probability of adoption based on the mean value of the expert ratings. To operationalize the supervised learning stage, the aggregated expert

Table 2. Participant demographics for ML-based feature importance assessment of blockchain adoption enablers

Attribute	*n*	Total	Attribute	*n*	Total
Years of experience			*Designation*		
20 + years	6		General manager	10	
15–19 years	10		Senior manager	16	
10–14 years	24		Manager	28	
6–9 years	30		Assistant manager	22	
		100			100
Educational qualification			*Industry domain*		
PhD	6		Automotive OEM	28	
Master's degree	56		EV supply chain startups	16	
Bachelor's degree	30		Automotive Tier 1 Suppliers	26	
Postgraduate diploma	8		Blockchain and IT consulting	30	
		100			100
Age group			*Gender*		
51+ years	2		Male	74	
41–50 years	8		Female	26	
31–40 years	30				
26–30 years	40				
22–25 years	20				
		100			100

Source(s): Author's own work

importance ratings were converted to a binary format to reflect the likelihood of adoption. Factors with a mean expert rating above the sample mean were coded as 1, while factors with a mean rating at or below the sample mean were coded as 0. This transformation allows the application of classification-based ML algorithms, which are appropriate for distinguishing high-priority adoption enablers from lower-impact factors while preserving the relative importance patterns identified in the expert ratings. A series of hyperparameter-tuned classifiers were used to benchmark predictive performance. The data set was split in an 80:20 ratio for training and testing, respectively, and all models were implemented using Python in the Google Colab environment.

The *RF* classifier was trained using “n_estimators = 1000” and “criterion = gini.” The *Logistic Regression (LR)* classifier used “solver = lbfgs” and “intercept_scaling = 1.” The *Support Vector Machine (SVM)* was configured with “C = 1” and “kernel = rbf.” The *K-Nearest Neighbors (KNN)* classifier used “n_neighbors = 5” and “metric = minkowski.” Subsequently, the BORUTA algorithm was applied to the RF model to eliminate irrelevant and low-impact enablers. BORUTA is a wrapper-based feature selection method that evaluates the statistical importance of each variable by comparing it against randomized shadow features. Enablers that consistently outperformed the shadow features were retained, while others were classified as tentative or rejected. To enhance the transparency of the methodology, the performance of the model was evaluated using accuracy, precision, recall and F1-score metrics on the test data set. Among the tested algorithms, the RF model demonstrated the highest stability in prediction and feature relevance, which justifies the choice of this model in the feature importance analysis.

Through iterative evaluation, BORUTA confirmed *12 enablers* as statistically significant, with *6 enablers classified as tentative* and *9 rejected*. These 12 validated enablers constitute the final input set for the subsequent TISM–MICMAC structural modeling phase. A detailed summary of the feature selection results, including normalized importance scores (Norm-Hits), is provided in Appendix Tables 3 and 4.

To assess the robustness of the feature selection process, ML models were retrained using only the selected enablers. The RF classifier consistently exhibited superior predictive performance relative to alternative classifiers, indicating that the reduced enabler set retained strong explanatory power. Detailed classifier performance results are reported in the supplementary material.

However, it should be emphasized that *BORUTA does not generate a ranked list of features* by default (Kursa and Rudnicki, 2010). It only distinguishes between confirmed, tentative and rejected features. Therefore, to *rank the BORUTA-selected enablers*, the RF classifier was reapplied to determine feature importance scores using the feature_importances_ attribute. This approach is supported by prior research (Chen *et al.*, 2020), where the model yielding the highest performance metrics is considered the most appropriate for final ranking.

Accordingly, Table 3 presents the final list of the top 12 enablers selected and ranked through this combined BORUTA–RF process. These enablers were further mapped under the PESTLE framework and used in the subsequent TISM–MICMAC structural analysis phase. This integration ensures that statistically validated enablers are structurally interpreted within the PESTLE-based contextual framework.

4.3 Interpretive structural modeling and MICMAC-based exploration of blockchain enabler interrelationships

The integration of ML in MCDM pipelines has recently gained attention in operations research for its ability to minimize subjectivity (Zhao *et al.*, 2021). By applying

Table 3. Top 12 blockchain adoption enablers (ranked by ML-based importance)

Rank	Enabler code	Enabler description	PESTLE dimension	Importance (%)
1	E17	Robust cybersecurity framework	Technological	7.71
2	E11	Customer experience enhancement and loyalty building	Social	5.23
3	E24	Comprehensive risk management and compliance framework	Legal	4.92
4	E20	Operational automation and efficiency enhancement	Technological	4.82
5	E18	Transparency and traceability frameworks	Technological	4.22
6	E6	Optimized supply chain and logistics management	Economic	4.20
7	E19	Innovative capabilities for competitive advantage	Technological	4.18
8	E12	Trust-Building collaborations and partnerships	Social	4.05
9	E28	Sustainable practices and corporate social responsibility	Environmental	3.92
10	E20	Quality assurance and authentication solutions	Social	3.85
11	E11	Cost optimization strategies and efficiency improvements	Economic	3.71
12	E1	Regulatory compliance and governance strategy	Political	3.39

Source(s): Author’s own work

BORUTA–RF prior to TISM–MICMAC, the current study aligns data-driven significance with interpretive expert modeling. This methodological fusion enhances the generalizability and reliability of prioritization, particularly in technology adoption contexts (Jain and Raj, 2016). Having finalized and ranked the top 12 enablers through the integrated BORUTA–RF process, the study proceeded to explore the interrelationships among these enablers using interpretive modeling techniques. For this purpose, the TISM and MICMAC analysis methodologies were used in the third phase of the research. A specialized panel of 20 experts was engaged to support this phase, representing diverse roles and organizations across the automotive and blockchain ecosystems. As detailed in Table 4, the experts hold senior leadership and strategic roles in renowned automotive OEMs and technology consulting firms, with extensive experience ranging from 10 to 25 years in supply chain digitization, blockchain integration and sustainability initiatives. Their insights were instrumental in capturing the nuanced dependencies and contextual relationships among the selected enablers, enabling a robust hierarchical model and categorization of drivers, linkages and dependent factors.

4.4 Hierarchical structuring of blockchain enablers using total interpretive structural modeling

The TISM hierarchy was developed by following the work of Warfield (1974) and then extended by Sushil in 2012. This model shows a five-level structure of things that help blockchain be used in supply chains. It goes from the things that are needed to the results that people want. It also shows how all these things are connected and affect the plan for putting blockchain to use [see Figure 2(a)] [The comprehensive computational results are presented in Appendix 4 (Tables A5–A10)].

Level 5: Foundational enablers (infrastructure layer)

At the base is the *Robust Cybersecurity Framework*, essential for maintaining data integrity and trust across decentralized networks. Without this layer, higher-level functions like traceability and governance lack credibility. As a cybersecurity head at Tata Motors stated, “Unless the system is cyber-resilient, no stakeholder will trust the ledger—especially across multiple tiers.”

Level 4: Governance and compliance enablers

The next layer includes *Comprehensive Risk Management and Compliance Framework and Regulatory Compliance and Governance Strategy*, which ensure alignment with legal and industry norms. In the heavily regulated automotive sector, these enable automation of compliance and strengthen trust across the supply chain. As a Hyundai project lead explained, “Governance and risk frameworks drive most of our digital decisions—we can’t deploy blockchain without board-level alignment.”

Level 3: Operational enablers (execution layer)

This level operationalizes blockchain through *Transparency and Traceability*, *Optimized Supply Chain and Logistics Management* and *Operational Automation and Efficiency*. These functions create visibility, enable real-time tracking and reduce manual efforts via smart contracts. A Škoda Auto supply chain manager observed, “With blockchain-based traceability, we’ve cut recall costs significantly—it’s a win for logistics and compliance both.”

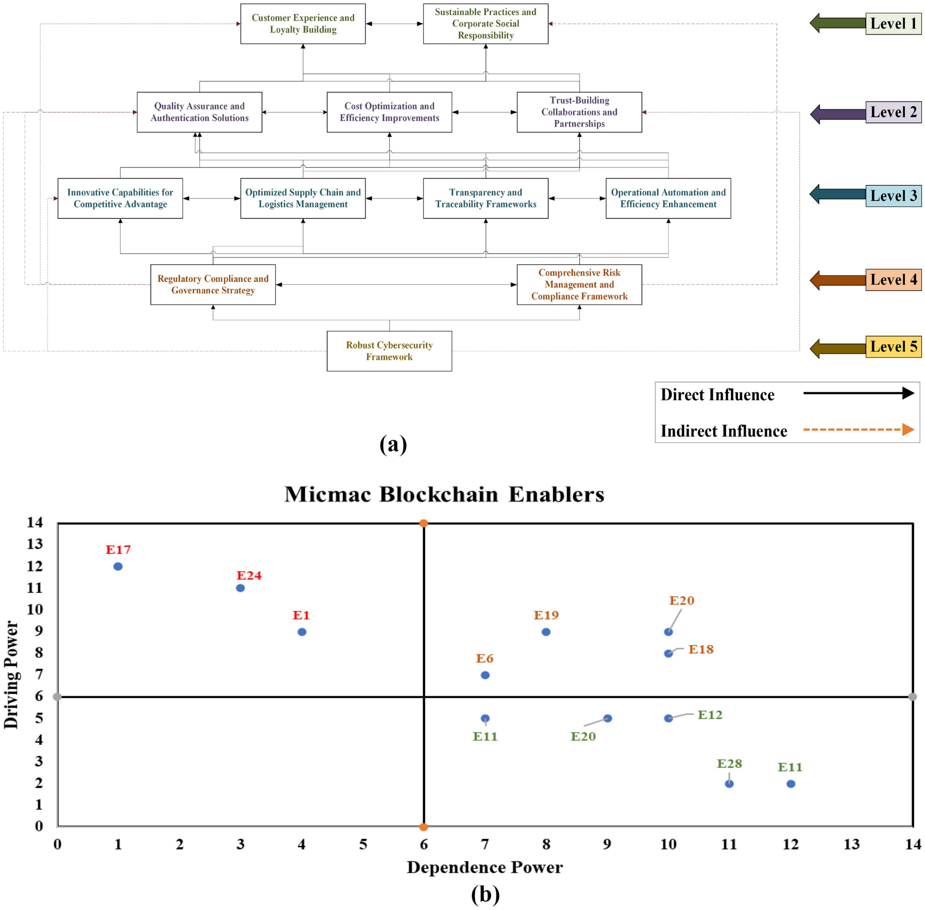
Level 2: Strategic performance enablers

These enablers – *Cost Optimization*, *Quality Assurance* and *Trust-Building Collaborations* – support organizational performance and reputation. Blockchain reduces redundancy and delays through secure automation. Quality validation via digital identifiers ensures authenticity and reduces counterfeiting. As a quality manager at BYD Auto noted,

Table 4. Expert panel composition for TISM–MICMAC analysis

Expert	Organization	Designation	Years of experience
E1	BYD Auto	Director of Digital Strategy	14
E2	Ford Motor Company	Senior Manager	20
E3	General Motors	Deputy General Manager	18
E4	Hyundai Motor India Ltd.	Manager	20
E5	Menza Motors Pvt. Ltd.	Digital Project Manager (Blockchain)	10
E6	NIO Inc.	Senior Blockchain Expert	15
E7	Rivian Automotive, Inc.	Manager	12
E8	Rivian Automotive, Inc.	Product Manager (Blockchain)	10
E9	Tata Consultancy Services	Engagement Director (Consulting and Service Integration)	25
E10	Tata Motors	Senior Manager	14
E11	Tata Motors	Deputy General Manager, Sustainability	13
E12	Tata Motors	Senior Manager	13
E13	Tesla, Inc.	Senior Manager	15
E14	Tesla, Inc.	Director (Smart Manufacturing and AI)	14
E15	Tesla, Inc.	Lead Consultant	11
E16	Xpeng Motors	Manager (EV Blockchain Integration)	13
E17	Škoda Auto Company	Assistant General Manager	25
E18	Škoda Auto Company	Chief Manager	15
E19	Škoda Auto Company	Chief Manager	12
E20	Škoda Auto Company	Deputy Manager	11

Source(s): Author’s own work



(a)

(b)

Figure 2. Integrated TISM–MICMAC analysis of blockchain adoption enablers in the automotive sector: (a) TISM-based hierarchical structural model showing multi-level relationships among enablers; (b) MICMAC analysis illustrating classification based on driving and dependence power

Source: Author’s own work

“Authentication of parts using blockchain is an immediate trust enabler—specifically with grey-market issues in EVs.”

These enablers also serve as feedback mechanisms that refine earlier layers like governance and compliance.

Level 1: Outcome-oriented enablers

At the top lie *Customer Experience Enhancement* and *Sustainable Practices and CSR* – the ultimate outcomes of successful blockchain adoption. Blockchain enables transparency into sourcing and emissions, reinforcing ethical operations and regulatory alignment. A Rivian ESG lead commented, “EV buyers today ask for sustainability proof—blockchain helps us transparently showcase our carbon and sourcing footprint.”

These capabilities enhance brand trust, improve recall responsiveness and support personalized services – hallmarks of a mature, blockchain-enabled ecosystem.

The TISM model also distinguishes between direct and indirect influences among enablers. For example:

- Traceability directly enables quality assurance;
- Regulatory compliance supports risk management; and
- Cybersecurity indirectly impacts sustainability by securing data used in ethical sourcing and carbon reporting.

These layered and transitive relationships underscore the complex, multi-tiered nature of blockchain adoption. The interpretive modeling approach of TISM allows these dependencies to be structured in a way that supports managerial insight and policy guidance.

4.5 MICMAC-based classification of blockchain enablers in the automotive supply chain

Blockchain adoption in automotive supply chains is a multi-stage transformation rather than a standalone upgrade. Success depends on strong foundations in governance, risk and cybersecurity before advancing to operational optimization and strategic differentiation. Manufacturers must prioritize foundational enablers while developing return on investment-driven use cases. The TISM framework helps map the sequential development of blockchain capabilities, offering a roadmap for implementation. This hierarchy also informs policymakers and industry stakeholders, enabling targeted interventions through standards for interoperability, cybersecurity and regulation. By clarifying influence flows, TISM offers both academic and practical guidance in navigating blockchain integration.

To further interpret systemic roles, MICMAC analysis was applied to the reachability matrix from TISM. It categorizes enablers into four groups – autonomous, dependent, linkage and driver – based on their influence and dependence. This classification identifies strategic levers and implementation priorities within the blockchain ecosystem, offering a system-level view of operational dynamics in automotive supply chains [see Figure 2(b)].

Of the 12 enablers considered, three were high-driving power drivers with low dependence, constituting the system structure. They are the Robust Cybersecurity Framework (E17), Comprehensive Risk Management and Compliance Framework (E24) and Regulatory Compliance and Governance Strategy (E1). The Robust Cybersecurity Framework (E17) was the system’s highest driving power. Since blockchain is based on decentralized architecture and the immutability of data, cybersecurity is the basis of trust. As a senior manager at Tata Motors would attest, “Unless the system is cyber-resilient, no stakeholder will trust the ledger—especially across multiple tiers.” Likewise, governance and compliance enablers (E24 and E1) are key to authenticating blockchain adoption across regulatory horizons and risk-sensitive operations. These anchor enablers do not rely heavily on other variables, demonstrating their independence and strategic importance.

The MICMAC analysis identified several *linkage enablers* – those with both high driving and dependence power – such as Innovative Capabilities for Competitive Advantage (E19), Optimized Supply Chain and Logistics Management (E6), Transparency and Traceability Frameworks (E18) and Quality Assurance and Authentication Solutions (E20). These enablers play a transitional role, bridging foundational technological factors with outcome-focused objectives. For example, E18 strengthens traceability and provenance tracking, but its effectiveness depends on cybersecurity and compliance frameworks. As an executive from Škoda Auto noted, “Blockchain traceability reduced our recall-related expenses significantly, but it only paid off once we had audit-ready risk frameworks and part authentication processes in place." Likewise, E6 and E19 enhance responsiveness and strategic differentiation but rely on prior infrastructure maturity.

In contrast, *dependent enablers* – Customer Experience Enhancement (E11), Trust-Building Collaborations (E12) and Sustainable Practices and CSR (E28) – exhibited high dependence and low driving power. These are visible outcomes of blockchain deployment and reflect downstream success. A product strategist from Rivian Automotive emphasized, "EV buyers today ask for sustainability proof—blockchain helps us transparently showcase our carbon and sourcing footprint." These enablers are essential for building stakeholder trust and competitive positioning, though they rely heavily on upstream implementation success.

No enablers were classified as *autonomous*, affirming the systemic interconnectivity of the model and validating the ML-based selection process. MICMAC enhances the TISM hierarchy by categorizing enablers into strategic groups, offering actionable insights. Driver enablers guide initial implementation, linkage enablers demand careful sequencing and dependent enablers serve as key performance indicators to evaluate performance and stakeholder impact.

5. Discussion

This study provides a sector-specific analysis of blockchain adoption in automotive supply chains, challenging one-size-fits-all adoption models (Chen *et al.*, 2020; Wissuwa and Durach, 2021). However, findings reveal that EVs use blockchain for the pursuit of sustainability and innovation, while TVs focus on cybersecurity and efficiency. From the institutional theory perspective, the difference in priorities can be explained in terms of legitimacy pressures and institutional environments for EVs and TVs, respectively. These findings extend institutional theory by demonstrating that legitimacy pressures do not uniformly drive blockchain adoption but instead reshape technological priorities depending on sectoral maturity and innovation trajectories. Likewise, the TOE framework is refined by showing that environmental pressures dominate adoption logic in emerging EV ecosystems, whereas organizational efficiency considerations remain central within legacy automotive structures. This sector-contingent interpretation advances prior studies that treated blockchain adoption drivers as homogeneous across industries.

From the findings, EVs are focused on sustainability, traceability and innovation in the context of BCT for ethical sourcing, product life cycle and circular economy strategies, respectively. This is in line with the environmental dimension of the TOE framework, in which sustainability pressures are external forces driving technology adoption in a particular industry or sector. This is consistent with earlier studies highlighting blockchain's value in green manufacturing (Angelopoulos *et al.*, 2023; Stark *et al.*, 2023; Singh *et al.*, 2022) but is contrary to assumptions about cost savings as a pan-industry driver. On the other hand, TVs are focused on cybersecurity and cost savings, which, from the RBV perspective, could mean these are capabilities for organizations to respond to external pressures in a structured supply chain for the pursuit of organizational success in a particular industry or sector (Agrawal *et al.*, 2021). This divergence suggests that blockchain adoption follows different value-creation logics across sectors: EV manufacturers pursue differentiation through sustainability signaling, whereas traditional manufacturers prioritize operational risk mitigation and cost rationalization.

Effective blockchain implementation depends on multi-stakeholder coordination across regulators, suppliers and customers to establish shared governance and data standards (Kouhizadeh and Sarkis, 2018). Without collective alignment, blockchain risks remaining fragmented and unable to deliver interoperability and trust. Concerns related to data privacy and smart contract governance further reinforce the importance of collaborative readiness (Korpela *et al.*, 2017). For consumer trust, businesses need to be transparent about operations, offer educational programs for consumers and ensure that their utilization of blockchain is in alignment with ethical data-sharing methods.

6. Implications

This study makes a substantial contribution to the literature on blockchain adoption within the automotive industry, with specific implications for researchers, managers and policymakers. By investigating the enablers of blockchain integration across both EV and TV manufacturing sectors, this article offers insights into how distinct operational needs influence blockchain adoption strategies.

6.1 Theoretical implications

This research presents a new theoretical contribution by suggesting a strong, hybrid approach to integrating supervised ML (RF, permutation importance and BORUTA) with interpretive modeling approaches (TISM and MICMAC) to rank and structure the enablers of blockchain adoption among automotive supply chains. In contrast to existing research that uses generalized ranking models or expert-based judgments, this method improves objectivity, rigor and context-relevance by filtering expert-identified enablers using a data-driven approach. The application of ML for ranking enablers and interpretive approaches for structural modeling presents a replicable and scalable methodological contribution to the technology adoption literature. Our results demonstrate that drivers of blockchain adoption differ markedly between conventional vehicle (TV) and EV manufacturing sectors. In particular, EV manufacturers value sustainability, traceability and innovation more – aligning blockchain deployment with objectives such as ethical raw material sourcing, lifecycle emissions and transparent carbon reporting. These rankings support the emerging literature on blockchain's potential to encourage green and circular manufacturing (Angelopoulos *et al.*, 2023; Singh *et al.*, 2022).

The hybrid framework extends TOE, institutional theory and RBV by demonstrating that blockchain adoption drivers are sector-contingent rather than uniform. Environmental legitimacy pressures dominate EV ecosystems, whereas capability-driven efficiency considerations shape adoption priorities in traditional manufacturing contexts. Meanwhile, TV makers focus more on operational enablers such as cost efficiency, cybersecurity controls and regulatory compliance. Here, the application of BCT is deliberately used to construct tamper-proof audit trails, improve the effectiveness of product recall and make regulatory records more reliable. This sector-specific focus difference reflects the importance of sector-specific adoption techniques instead of a one-for-all approach, an area often overlooked by existing models (Chen *et al.*, 2020; Wissuwa and Durach, 2021).

By integrating TISM and MICMAC, the study advances systems-level understanding of hierarchical and driving-dependence relationships among blockchain enablers, contributing structural depth to technology adoption research. This multi-level structure is a contribution to the TOE framework in that it explains the influence of environmental pressures, organizational capabilities and technology enablers on the adoption of BCT in the EV ecosystem.

6.2 Managerial implications

The practical insights from this research bear important implications for supply-chain managers, technology leaders and strategists within the automotive industry. Recognizing Robust Cybersecurity Framework as a priority enabler, it implies, from the RBV perspective, that cybersecurity is a digital capability for organizations to sustain their competitive advantage in a particular industry or sector. The emphasis placed on Transparency and Traceability Frameworks by EV manufacturers and TV manufacturers underlines the necessity for effective end-to-end visibility solutions enabling firms to ascertain component traceability throughout the production process. Such capabilities would ensure compliance with the stipulations of the industry standards and instate trust among supply partners through the availability of verifiable data pertaining to origin, quality and handling.

For EV manufacturers, the promise of blockchain in fostering sustainable practices and corporate social responsibility provides the opportunity for strategic maneuvering to enhance brand equity in compliance with the mindset of eco-conscious consumers. Managers can use blockchain transparency for championing opaque accountability of ethical sourcing of raw materials along with tracing environmental impact throughout manufacturing, which implies commitment toward sustainability. This commitment to sustainability objectives increases the prospects for EV manufacturers to attract environmentally conscious consumers and aligns with emerging consumer preferences for sustainable products.

In contrast, TV manufacturers can look at blockchain for cost optimization strategies and efficiency improvements by exploiting blockchain to ensure streamlined operations, automatic task execution through smart contracts and minimal human interference. Particularly, smart contracts pave the way for the reduction of transaction costs, elimination of intermediaries and a reduction of human error, which is critical for an industry operating with lean production and cost efficiency. These insights may directly help managers in the traditional manufacturing sector develop blockchain-based solutions for efficiency, cost-focused operations and value addition in a price-sensitive market. The key takeaways for policymakers and industry stakeholders regarding blockchain adoption in the automotive supply chain are summarized in Table 5.

These policy recommendations are in line with the environmental dimension of the TOE framework in explaining the influence of regulatory structures on technology adoption in a particular industry or sector, especially in the context of a complex automotive ecosystem. These findings, therefore, suggest that policymakers are quite instrumental in influencing the regulatory framework that governs blockchain adoption. This goes without saying since it is the strategy of Regulatory Compliance and Governance that would drive blockchain adoption, which could unveil clear guidelines on data privacy, cybersecurity and interoperability standards. Policy guidance on blockchain data standards and regulatory compliance will be critical in enabling the leap toward this decentralized and secure data-sharing framework that benefits all participants in the automotive supply chain.

7. Conclusion and future directions

This study proposes a novel, hybrid model for identification and structuring of the facilitators of blockchain adoption in automobile supply chains, considering both electric and conventional vehicle manufacturers through a comparative research design. Through the coupling of ML techniques (RF, permutation importance and BORUTA) and TISM and MICMAC analysis, this study proposes a robust and replicable approach for technology adoption studies. Its findings reveal that EV manufacturers relate blockchain adoption to sustainability, innovation and traceability objectives, whereas conventional vehicle manufacturers emphasize cost-effectiveness, cybersecurity and regulatory compliance. The hierarchy derived through TISM places the highest priority on cybersecurity and governance strategies, whereas MICMAC classification identifies key driver enablers that influence subsequent adoption outcomes.

This research contributes to theory by bringing together data-driven priority with structure modeling guided by experts. Practically, it provides auto managers with a strategic way of balancing blockchain initiatives with industry goals and operational requirements. For policymakers, the research offers useful guidelines for structuring supportive regulation, encouraging responsible sourcing practices and enabling interoperability.

Table 5. Takeaways for policymakers and industry stakeholders

Category	Demand-level	Supply-level	Actionable steps
Strategies	*Data security and cyber resilience*: Strengthening blockchain-based cybersecurity frameworks will enhance data protection across supply chains. EV and TV manufacturers must adopt decentralized ledger systems for tamper-proof data integrity	*Regulatory framework for blockchain interoperability*: The government should establish standardized regulations for blockchain adoption, ensuring compatibility across suppliers, manufacturers and global markets	(Short-term) Automakers should start with pilot implementations of blockchain security protocols, while policymakers can introduce sandbox regulatory models to test interoperability
	Transparency and traceability for trust: Blockchain-enabled real-time tracking of automobile components and raw materials can reduce counterfeiting and enhance supply chain visibility. Manufacturers must integrate IoT-based blockchain systems for automated traceability verification	*Smart contracts for automated compliance*: Expanding smart contract adoption across EV and TV manufacturers can reduce transaction costs, minimize disputes and streamline procurement. Governments should provide regulatory clarity on smart contract enforceability	(Medium-term) Set compliance deadlines for blockchain-based traceability systems in automotive parts manufacturing. Governments should release legally binding guidelines on smart contract validity
	Ethical and social responsibility in blockchain adoption: Blockchain implementation must align with ethical sourcing, responsible data governance and consumer privacy concerns. Transparent and ethical data usage will enhance consumer trust in blockchain-enabled traceability solutions	Automakers and policymakers must establish blockchain ethics standards, balancing transparency with data confidentiality to protect stakeholders while fostering supply chain accountability	(Short-term) Establish consumer education initiatives and ethical data-sharing protocols. (Medium-term) Introduce industry-wide blockchain ethics certification. (Long-term) Develop cross-sector blockchain governance alliances

(*continued*)

Table 5. Continued

Category	Demand-level	Supply-level	Actionable steps
Drivers	*Sustainability and ethical sourcing in EV manufacturing*: Consumers increasingly demand eco-friendly vehicles with verified ethical material sourcing. Blockchain can provide full transparency in sourcing lithium, cobalt and other critical materials	*Infrastructure for blockchain integration*: Automakers require scalable blockchain networks that integrate with existing ERP systems. Governments and tech firms must collaborate to develop secure, high-speed blockchain nodes to support automotive data exchange	(Long-term) incentivize automakers to adopt blockchain-based sustainability certifications. Establish joint ventures between automakers and cloud technology providers to create a secure blockchain network
	Cost optimization and lean manufacturing for TVs: TV manufacturers prioritize cost efficiency and process automation. Blockchain allows automated supplier payments and real-time inventory updates, ensuring leaner manufacturing and reduced administrative overhead	*Public–private partnerships (PPP) for blockchain development*: Industry collaboration is essential for blockchain research and development. Governments should support incentives for blockchain integration, encouraging multi-stakeholder engagement	(Short-term) Industry players should form blockchain consortiums to pool resources and reduce development costs. Governments should offer tax breaks for manufacturers implementing blockchain in production efficiency

Source(s): Author's own work

Future studies can also apply this framework to other high-complexity industries like pharmaceuticals and electronics, where traceability and compliance are equally essential. The integration of blockchain with Internet of Things and artificial intelligence will also enable real-time decision-making, predictive maintenance and improved supply chain intelligence. Global data privacy norms research, smart contract enforceability research and cross-border compliance research will also continue to develop blockchain implementation strategies. Finally, this research sets the stage for sustainable, adaptive and digitally resilient supply chains fueled by BCT.

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Appendix 1

Section 1: Detailed list of blockchain adoption enablers in the automotive sector

This appendix section presents a comprehensive list of the 30 key enablers that influence blockchain adoption in the automotive industry. These enablers were identified through an extensive review of academic literature and validated through expert consultation. Each enabler is explained with respect to its relevance in the automotive context, and supported with real-world applications by major automotive firms. This section provides additional clarity on how these enablers manifest in practice and supports the rationale for their inclusion in the subsequent modeling and analysis phases of the study.

Table A1. Blockchain enablers in the automotive sector with definitions and industry applications

Code	Enabler	Explanation	Automotive company application
E1	Regulatory compliance and governance strategy	Ensures compliance with safety and emissions laws	BMW uses blockchain to track cobalt sourcing to meet EU conflict mineral laws
E2	Standardization across platforms	Promotes compatibility across supply chain systems	Mobility open blockchain initiative (MOBI), led by Ford and BMW, is working on standards
E3	Interoperability with legacy systems	Allows connection with existing ERP/PLM tools	Volkswagen integrates blockchain with SAP for supply chain tracking
E4	Public and private partnership support	Encourages blockchain via government-backed programs	Renault works with the French Government to test blockchain for vehicle compliance
E5	Blockchain-ready infrastructure	Includes IoT, Cloud and 5G readiness	Tesla deploys edge IoT devices and private blockchain for in-house logistics
E6	Optimized supply chain and logistics management	Enhances part flow and reduces logistics issues	Volvo uses blockchain to track lithium battery materials
E7	Scalable digital platforms	Scales blockchain across plants and partners	Toyota's blockchain lab developed scalable ledgers for parts and insurance
E8	Automated auditing and reporting systems	Smart contracts support regulatory and warranty logs	Renault launched a blockchain for vehicle compliance certification (XCEED project)
E9	Smart contract maturity and integration	Automates leasing, service contracts and finance	Daimler tested Ethereum smart contracts for auto financing in Singapore
E10	Real-time data integration	Connects sensors and vehicles for live tracking	General Motors (GM) filed patents for blockchain + IoT vehicle data sharing
E11	Cost optimization strategies	Reduces costs from intermediaries and recalls	Ford uses blockchain for supply traceability and recall cost reduction
E12	Trust-building collaborations	Enhances OEM-supplier-logistics trust	Hyundai MOBIS uses blockchain to improve parts authentication
E13	Stakeholder awareness and readiness	Encourages smooth adoption among users	Bosch conducts blockchain training for suppliers and managers
E14	Customer experience and loyalty building	Increases brand trust via transparent service history	Jaguar Land Rover rewards drivers with crypto tokens for sharing driving data

(*continued*)

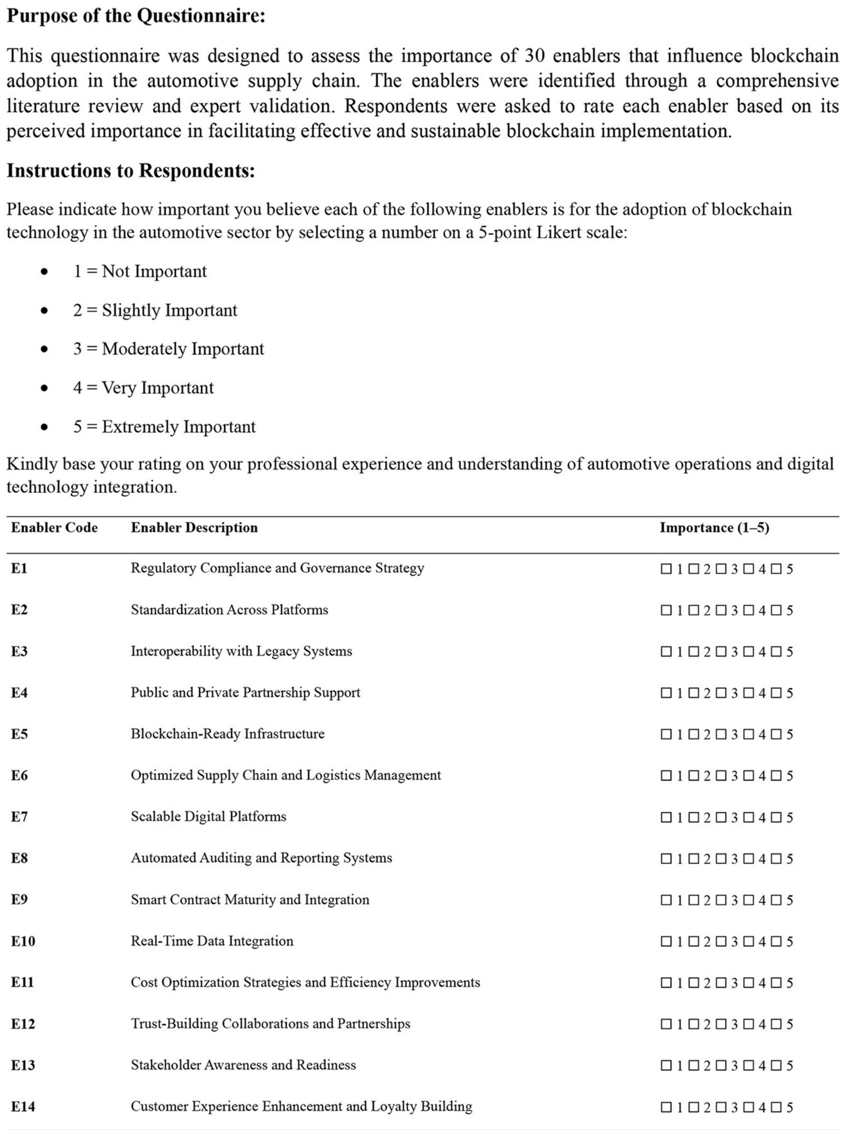
Table A1. Continued

Code	Enabler	Explanation	Automotive company application
E15	Organizational commitment	Leadership and culture push blockchain pilots	Volkswagen Group’s investment arm supports blockchain startups like Minespider
E16	Data ownership and accessibility	Role-based secure access to sensitive data	Porsche uses blockchain for secure car access and personalization data
E17	Robust cybersecurity framework	Prevents data theft in connected vehicles	Tesla uses cryptographic blockchain principles in over-the-air updates
E18	Transparency and traceability	End-to-end part traceability ensures quality	BMW’s “PartChain” tracks components from origin to assembly
E19	Innovation for competitive advantage	Drives new services and digital models	Toyota explores blockchain for vehicle usage-based insurance and car sharing
E20	Operational automation	Removes manual steps in supply chain processes	Bosch uses smart contracts to automate supplier payments
E21	Financial and investment readiness	Budget support for pilot and enterprise adoption	Hyundai AutoEver invested in blockchain infrastructure development
E22	Legal and regulatory uncertainty	Legal clarity improves adoption planning	European automobile manufacturers association (ACEA) is working on legal frameworks
E23	Technological obsolescence risk	Future-ready architecture reduces fear of tech failure	Daimler builds modular blockchain tools to adapt to evolving protocols
E24	Comprehensive risk and compliance framework	Merges blockchain into ERM, audits and recalls	Renault integrates compliance and risk into blockchain for supply traceability
E25	Cultural resistance and barriers	Change management helps overcome resistance	Ford conducted change workshops during the blockchain pilot rollout
E26	Privacy-enhancing technologies (PETs)	Protects sensitive vehicle/user data while maintaining verifiability	BMW and Ocean Protocol use PETs to anonymize supply chain data
E27	Decentralized identity management	Ensures secure vehicle and driver ID management	Volkswagen tested blockchain IDs for mobility-as-a-service (MaaS) platforms
E28	Sustainable practices and CSR	Tracks ESG performance and lifecycle footprint	Volvo tracks ethical sourcing of cobalt and battery recycling with blockchain
E29	Vendor and supplier readiness	Ensures third-party integration and compatibility	Toyota developed supplier readiness templates for blockchain onboarding
E30	Blockchain education and talent availability	Supports adoption through skilled professionals	Renault and Deloitte host training programs for blockchain integration

Note(s): EU = European union; SAP = Systems, applications, and products; ID = Identification; ERP = Enterprise resource planning; PLM = Product lifecycle management

Appendix 2. Ranking of blockchain adoption enablers in the automotive sector using random forest and BORUTA algorithm

Section B1: Questionnaire used for evaluating blockchain adoption enablers in the automotive sector



Purpose of the Questionnaire:

This questionnaire was designed to assess the importance of 30 enablers that influence blockchain adoption in the automotive supply chain. The enablers were identified through a comprehensive literature review and expert validation. Respondents were asked to rate each enabler based on its perceived importance in facilitating effective and sustainable blockchain implementation.

Instructions to Respondents:

Please indicate how important you believe each of the following enablers is for the adoption of blockchain technology in the automotive sector by selecting a number on a 5-point Likert scale:

- 1 = Not Important
- 2 = Slightly Important
- 3 = Moderately Important
- 4 = Very Important
- 5 = Extremely Important

Kindly base your rating on your professional experience and understanding of automotive operations and digital technology integration.

Enabler Code	Enabler Description	Importance (1–5)
E1	Regulatory Compliance and Governance Strategy	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E2	Standardization Across Platforms	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E3	Interoperability with Legacy Systems	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E4	Public and Private Partnership Support	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E5	Blockchain-Ready Infrastructure	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E6	Optimized Supply Chain and Logistics Management	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E7	Scalable Digital Platforms	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E8	Automated Auditing and Reporting Systems	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E9	Smart Contract Maturity and Integration	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E10	Real-Time Data Integration	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E11	Cost Optimization Strategies and Efficiency Improvements	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E12	Trust-Building Collaborations and Partnerships	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E13	Stakeholder Awareness and Readiness	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E14	Customer Experience Enhancement and Loyalty Building	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

(*continued*)

Enabler Code	Enabler Description	Importance (1–5)
E15	Organizational Commitment and Digital Culture	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E16	Data Ownership and Accessibility	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E17	Robust Cybersecurity Framework	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E18	Transparency and Traceability Frameworks	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E19	Innovative Capabilities for Competitive Advantage	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E20	Operational Automation and Efficiency Enhancement	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E21	Financial and Investment Readiness	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E22	Legal and Regulatory Uncertainty	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E23	Technological Obsolescence Risk	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E24	Comprehensive Risk Management and Compliance Framework	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E25	Cultural Resistance and Adoption Barriers	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E26	Privacy-Enhancing Technologies	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E27	Decentralized Identity Management	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E28	Sustainable Practices and Corporate Social Responsibility	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E29	Vendor and Supplier Blockchain Readiness	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
E30	Blockchain Education and Talent Availability	☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section B2: Feature importance ranking of blockchain enablers based on expert ratings

This appendix section presents the prioritization results of the 30 identified enablers for blockchain adoption in the automotive sector. The rankings were derived using expert inputs collected through a structured Likert-scale questionnaire. Participants were asked to rate each enabler based on its perceived importance for successful blockchain implementation. The collected data was then processed using a feature-ranking method (e.g. random forest/BORUTA/PERMIMP), and the top 12 enablers were shortlisted for further modeling and analysis (as presented in the main study).

Table A2. Importance ranking of blockchain adoption enablers in the automotive sector

Enabler code	Enabler description	Rank	Importance (%)
E1	Regulatory compliance and governance strategy	30	3.39
E2	Standardization across platforms	19	2.75
E3	Interoperability with legacy systems	26	2.53
E4	Public and private partnership support	18	2.98
E5	Blockchain-ready infrastructure	11	3.12
E6	Optimized supply chain and logistics management	6	4.20
E7	Scalable digital platforms	12	3.10
E8	Automated auditing and reporting systems	16	2.85
E9	Smart contract maturity and integration	17	2.80
E10	Real-rime data integration	14	2.92
E11	Cost optimization strategies and efficiency improvements	10	3.71
E12	Trust-building collaborations and partnerships	8	4.05
E13	Stakeholder awareness and readiness	22	2.65
E14	Customer experience enhancement and loyalty building	4	5.23
E15	Organizational commitment and digital culture	13	2.94
E16	Data ownership and accessibility	20	2.70
E17	Robust cybersecurity framework	1	7.71
E18	Transparency and traceability frameworks	5	4.22
E19	Innovative capabilities for competitive advantage	7	4.18
E20	Operational automation and efficiency enhancement	3	4.82
E21	Financial and investment readiness	23	2.63
E22	Legal and regulatory uncertainty	27	2.45
E23	Technological obsolescence risk	28	2.40
E24	Comprehensive risk management and compliance framework	2	4.92
E25	Cultural resistance and adoption barriers	29	2.38
E26	Privacy-enhancing technologies	24	2.60
E27	Decentralized identity management	25	2.55
E28	Sustainable practices and corporate social responsibility	9	3.92
E29	Vendor and supplier blockchain readiness	15	2.88
E30	Blockchain education and talent availability	21	2.69

Section B3: BORUTA feature selection results for blockchain enablers

To enhance the robustness of feature selection and reduce subjectivity in ranking, the BORUTA algorithm was applied to the expert-rated data set. BORUTA is a wrapper-based feature selection method that iteratively compares actual features with randomized shadow features using a random forest classifier. The algorithm classifies variables into three categories:

- ✓ *Confirmed* – Enablers consistently important across iterations;
- ? *Tentative* – Enablers with borderline or uncertain importance; and
- × *Rejected* – Enablers found consistently unimportant.

The output of this analysis provides a refined basis for identifying the most critical enablers for blockchain adoption in the automotive supply chain.

BORUTA application summary:

After multiple iterations, BORUTA:

- *Confirmed* 15 enablers as important;
- *Marked* 6 enablers as tentative; and
- *Rejected* 9 enablers due to low importance.

The Norm-Hits (%) column in the table below refers to the normalized frequency (0–100%) with which each enabler was marked as important during the iterative runs of the BORUTA algorithm.

Table A3. BORUTA feature selection output for blockchain enablers

Enabler code	Norm-Hits (%)	BORUTA status
E1	67	Tentative
E2	72	Tentative
E3	38	Rejected
E4	75	Tentative
E5	85	Confirmed
E6	91	Confirmed
E7	82	Confirmed
E8	64	Tentative
E9	60	Rejected
E10	70	Tentative
E11	88	Confirmed
E12	92	Confirmed
E13	42	Rejected
E14	90	Confirmed
E15	63	Rejected
E16	41	Rejected
E17	100	Confirmed
E18	93	Confirmed
E19	89	Confirmed
E20	95	Confirmed
E21	40	Rejected
E22	36	Rejected
E23	39	Rejected
E24	98	Confirmed
E25	34	Rejected
E26	66	Tentative
E27	61	Rejected
E28	87	Confirmed
E29	65	Tentative
E30	69	Tentative

Note(s): The 15 confirmed enablers served as the pool from which the top 12 were selected (based on importance scores) for the TISM–MICMAC modeling

Appendix 3. Final selection of blockchain enablers for TISM–MICMAC modeling

Following the feature importance ranking (Appendix B3) and BORUTA feature selection analysis (Appendix Section B3), a refined subset of 12 enablers was shortlisted for interpretive structural modeling (ISM) and MICMAC analysis. These enablers were selected based on their high normalized importance scores and their classification as “*Confirmed*” in the BORUTA output.

The selection reflects a balance between *technological feasibility*, *organizational value* and strategic relevance for blockchain implementation in the automotive supply chain. These enablers served as the input variables for developing the structural model and driver-dependence analysis.

Table A4. Final 12 blockchain enablers selected for TISM–MICMAC modeling

S. no.	Enabler code	Enabler description	Importance (%)	Original rank
1	E17	Robust cybersecurity framework	7.71	1
2	E24	Comprehensive risk management and compliance framework	4.92	2
3	E20	Operational automation and efficiency enhancement	4.82	3
4	E14	Customer experience enhancement and loyalty building	5.23	4
5	E18	Transparency and traceability frameworks	4.22	5
6	E6	Optimized supply chain and logistics management	4.20	6
7	E19	Innovative capabilities for competitive advantage	4.18	7
8	E12	Trust-building collaborations and partnerships	4.05	8
9	E28	Sustainable practices and corporate social responsibility	3.92	9
10	E11	Cost optimization strategies and efficiency improvements	3.71	10
11	E5	Blockchain-ready infrastructure	3.12	11
12	E7	Scalable digital platforms	3.10	12

Note(s): These 12 enablers represent the most critical success factors for blockchain adoption in the automotive supply chain as validated through a multi-method approach. They form the foundation for building the hierarchical structure and driver-dependence matrix used in the ISM-MICMAC methodology, presented in the following appendices

Appendix 4. Section E: TSIM and MICMAC calculations

The steps of TISM are as follows

Structural self-interaction matrix (SSIM).

SSIM is developed based on the contextual relationship established between barriers represented as i and j. According to Sage (1977), the relationship between any two variables, in our case barriers, can be represented by four standard symbols (V, X, A and O), which would help in giving a direction to the flow of the relationship. This representation is depicted in Table A1.

Table A5. Conversion algorithms for SSIM to initial reachability matrix

Representative symbols	i → j	j → i	(i,j)th entry	(j,i)th entry
V	✓	×	1	0
A	×	✓	0	1
X	✓	✓	1	1
O	×	×	0	0

Once SSIM is developed, it should be further discussed with opinion experts so that the result of SSIM is validated. Table A2 depicts the SSIM of the enablers of *blockchain* implementation in the automobile sector.

Table A6. Structural self-interaction matrix (SSIM) (blockchain enablers)

Variables	1	2	3	4	5	6	7	8	9	10	11	12
Lack of strategy and scenario planning in IoT	–	V	V	V	X	V	V	A	A	A	A	A
Lack of security		–	X	V	A	V	V	A	A	A	A	A
Difficulty of consequences prediction			–	V	A	V	X	A	A	A	A	A
Storage issues				–	A	X	A	A	A	A	A	A
Lack of privacy					–	V	V	A	A	X	A	A
Energy demands						–	A	A	A	A	A	A
Waste disposal							–	A	A	A	A	A
Legal framework for IoT governance								–	X	V	V	A
Trust creation and user acceptance									–	V	V	A
Dynamic environment										–	X	A
Scalability and interoperability											–	A
Cost												–

Table A7. Initial reachability matrix (blockchain enablers)

Variables	4	6	2	3	7	1	5	10	11	8	9	12	Driving power
Sustainable practices and corporate social responsibility	1	1	0	0	0	0	0	0	0	0	0	0	2
Customer experience enhancement and loyalty building	1	1	0	0	0	0	0	0	0	0	0	0	2
Trust-building collaborations and partnerships	1	1	1	1	1	0	0	0	0	0	0	0	5
Cost optimization strategies and efficiency improvements	1	1	1	1	1	0	0	0	0	0	0	0	5
Quality assurance and authentication solutions	1	1	0	1	1	0	0	0	0	0	0	0	4
Innovative capabilities for competitive advantage	1	1	1	1	1	1	1	0	0	0	0	0	7
Optimized supply chain and logistics management	1	1	1	1	1	1	1	1	0	0	0	0	8
Transparency and traceability frameworks	1	1	1	1	1	1	1	1	1	0	0	0	9
Operational automation and efficiency enhancement	1	1	1	1	1	1	1	1	1	0	0	0	9
Regulatory compliance and governance strategy	1	1	0	1	1	1	1	1	1	1	1	0	10
Comprehensive risk management and compliance framework	1	1	0	0	0	1	1	1	1	1	1	0	8
Robust cybersecurity framework	1	1	1	1	1	1	1	1	1	1	1	1	12
Dependence power	12	12	10	10	10	7	7	7	7	3	3	1	

Table A8. Final reachability matrix (blockchain enablers)

Variables	4	6	2	3	7	1	5	10	11	8	9	12	Driving power
Sustainable practices and corporate social responsibility	1	1	0	0	0	0	0	0	0	0	0	0	2
Customer experience enhancement and loyalty building	1	1	0	0	0	0	0	0	0	0	0	0	2
Trust-building collaborations and partnerships	1	1	1	1	1	0	0	0	0	0	0	0	5
Cost optimization strategies and efficiency improvements	1	1	1	1	1	0	0	0	0	0	0	0	5
Quality assurance and authentication solutions	1	1	1*	1	1	0	0	0	0	0	0	0	5
Innovative capabilities for competitive advantage	1	1	1	1	1	1	1	1*	1*	0	0	0	9
Optimized supply chain and logistics management	1	1	1	1	1	1	1	1	1*	0	0	0	9
Transparency and traceability frameworks	1	1	1	1	1	1	1	1	1	0	0	0	9
Operational automation and efficiency enhancement	1	1	1	1	1	1	1	1	1	0	0	0	9
Regulatory compliance and governance strategy	1	1	1*	1	1	1	1	1	1	1	1	0	11
Comprehensive risk management and compliance framework	1	1	1*	1*	1*	1	1	1	1	1	1	0	11
Robust cybersecurity framework	1	1	1	1	1	1	1	1	1	1	1	1	12
Dependence power	12	12	10	10	10	7	7	7	7	3	3	1	

Note(s): * Indicates transitive relationships (indirect links derived through transitivity)

Level partitions: Upon the completion of the formation of the final reachability set, the sets known as reachability set, antecedent set and intersection set are generated in line with the established procedure. Following the compilation of this table, a subsequent iteration is conducted to eliminate barriers that share a common reachability set at an intersection set. This process successfully determines the level of importance as the initial elimination of barriers, which is given high priority in the interpretive structural modeling (ISM) methodology. The aforementioned procedure persists until all facilitators and obstacles are allocated to their respective tiers inside the ISM model, hence generating the directed graph. Table A5 illustrates the level partitioning for the factors that hinder the adoption of Internet of Things (IoT) in the automotive industry. Whereas Table A6 shows the final reduced conical matrix, which is used to draw the final TISM model.

Table A9. Level partitioning (LP) blockchain enablers

Elements (Mi)	Reachability set R(Mi)	Antecedent set A(Ni)	Intersection set R(Mi)∩A(Ni)	Level
1	1, 5, 10, 11	1, 5, 8, 9, 10, 11, 12	1, 5, 10, 11	3
2	2, 3, 7	1, 2, 3, 5, 7, 8, 9, 10, 11, 12	2, 3, 7	2
3	2, 3, 7	1, 2, 3, 5, 7, 8, 9, 10, 11, 12	2, 3, 7	2
4	4, 6	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	4, 6	1
5	1, 5, 10, 11	1, 5, 8, 9, 10, 11, 12	1, 5, 10, 11	3
6	4, 6	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	4, 6	1
7	2, 3, 7	1, 2, 3, 5, 7, 8, 9, 10, 11, 12	2, 3, 7	2
8	8, 9	8, 9, 12	8, 9	4
9	8, 9	8, 9, 12	8, 9	4
10	1, 5, 10, 11	1, 5, 8, 9, 10, 11, 12	1, 5, 10, 11	3
11	1, 5, 10, 11	1, 5, 8, 9, 10, 11, 12	1, 5, 10, 11	3
12	12	12	12	5

Table A10. Reduced conical matrix (CM) blockchain enablers

Variables	4	6	2	3	7	1	5	10	11	8	9	12	Driving power	Level
Sustainable practices and corporate social responsibility	1	1	0	0	0	0	0	0	0	0	0	0	2	1
Customer experience enhancement and loyalty building	1	1	0	0	0	0	0	0	0	0	0	0	2	1
Trust-building collaborations and partnerships	1	1	1	1	1	0	0	0	0	0	0	0	5	2
Cost optimization strategies and efficiency improvements	1	1	1	1	1	0	0	0	0	0	0	0	5	2
Quality assurance and authentication solutions	1	1	1*	1	1	0	0	0	0	0	0	0	5	2
Innovative capabilities for competitive advantage	1	1	1	1	1	1	1	1*	1*	0	0	0	9	3
Optimized supply chain and logistics management	1	1	1	1	1	1	1	1	1*	0	0	0	9	3
Transparency and traceability frameworks	1	1	1	1	1	1	1	1	1	0	0	0	9	3
Operational automation and efficiency enhancement	1	1	1	1	1	1	1	1	1	0	0	0	9	3
Regulatory compliance and governance strategy	1	1	1*	1	1	1	1	1	1	1	1	0	11	4
Comprehensive risk management and compliance framework	1	1	1*	1*	1*	1	1	1	1	1	1	0	11	4
Robust cybersecurity framework	1	1	1	1	1	1	1	1	1	1	1	1	12	5
Dependence power	12	12	10	10	10	7	7	7	7	3	3	1		

Note(s): * Indicates transitive relationships (indirect links derived through transitivity)