IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 59, No. 3, March, 2026, pp. 839-854
Journal homepage: http://ieta.org/journals/jesa

A Trust-Driven Blockchain Framework for Securing Cleaner Energy Supply Chains: Evidence from Power Plant Spare Parts Systems

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https://doi.org/10.18280/jesa.590325

Received: 17 January 2026
Revised: 9 March 2026
Accepted: 19 March 2026
Available online: 31 March 2026

Keywords:
blockchain adoption, technology-mediated trust, Partial Least Squares Structural Equation Modeling, Unified Theory of Acceptance and Use of Technology, Information Systems Success, energy supply chain, risk awareness paradox, power plant spare parts

ABSTRACT

Counterfeit and substandard components in power plant spare part supply chains pose critical risks to operational reliability and environmental performance. This study develops and empirically validates a blockchain adoption framework that integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) with DeLone and McLean's Information Systems Success (ISS) model, positioning Trust in Blockchain Technology (TBT) as a central governance mechanism mediating the relationship between system perceptions and adoption behavior. The framework extends conventional UTAUT models by incorporating Perceived Traceability (PT) as a domain-specific construct and Top Management Support (TMS) as an organizational enabler. Empirical validation was conducted using survey data from 199 professionals in Indonesia's power generation and industrial supply chain sectors, analyzed through variance-based Partial Least Squares Structural Equation Modeling (PLS-SEM). The results reveal that Information Systems Success (ISS) ($\beta = 0.252$, $p = 0.001$) and Effort Expectancy (EE) ($\beta = 0.168$, $p = 0.021$) are the primary drivers of TBT, while Performance Expectancy (PE) ($\beta = 0.110$, $p = 0.145$), Perceived Traceability (PT) ($\beta = 0.063$, $p = 0.475$), and Social Influence (SI) ($\beta = -0.009$, $p = 0.898$) were not significant. TBT significantly mediates Behavioral Intention (BI) ($\beta = 0.313$, $p < 0.001$), which strongly predicts Use Behavior (UB) ($\beta = 0.775$, $p < 0.001$). Notably, Perceived Risk (PR) demonstrates a significant positive effect on BI ($\beta = 0.386$, $p < 0.001$), suggesting a 'Risk Awareness Paradox' wherein professionals with greater technological understanding simultaneously perceive higher risks and stronger adoption intentions. TMS directly influences UB ($\beta = 0.103$, $p = 0.025$) but does not moderate the intention–behavior relationship ($\beta = -0.019$, $p = 0.576$). The model explains 19.3% of the variance in TBT, 34.9% in BI, and 69.2% in UB. These findings challenge the assumption that traceability and performance are the dominant adoption drivers in industrial contexts, instead highlighting that system quality and usability underpin technology-mediated trust in energy supply chains. The study offers theoretical contributions to contextualized technology adoption and practical implications for blockchain implementation strategies in critical industrial sectors.

1. INTRODUCTION

Modern global supply chains, particularly those for critical power generation infrastructure, face increasingly complex challenges. The infiltration of illicit or counterfeit components into the supply chain poses dual risks: substantial economic losses and a critical threat to energy sustainability goals. Deploying substandard parts directly undermines combustion performance and increases carbon emissions. Issues such as product counterfeiting, lack of visibility in shipments, and technical data discrepancies not only cause significant financial losses but also pose severe threats to energy efficiency and environmental safety [1]. The use of substandard or counterfeit spare parts in power plants leads to suboptimal combustion efficiency, increased greenhouse gas emissions, and premature equipment disposal, directly contradicting the principles of cleaner logistics and the Circular Economy [2].

The failure of a single critical component can cause days of production-line downtime, resulting in millions of dollars in losses and potential environmental hazards from unstable plant operations. In this high-risk environment, blockchain technology appears as a transformative solution, providing a decentralized system that ensures authenticity, traceability, and data integrity through an immutable ledger. Unlike blockchain uses in the consumer-facing (B2C) market, which focus on convenience, deploying blockchain in industrial B2B settings—especially power plant supply chains—addresses a more urgent need: overcoming governance and trust issues that hinder sustainable operations [3, 4]. From a systems perspective, blockchain can be conceptualized as a digital infrastructure layer that enables end-to-end traceability, real-time verification, and secure data synchronization across distributed supply chain nodes.

For example, in Indonesia's energy manufacturing industries, procuring genuine spare parts is a top priority for maintaining clean production standards and operational reliability. A blockchain-based platform can verify every step of a spare part's journey, from the manufacturer to the final installation at the facility, creating a "digital passport" for each component. This 'digital passport' is crucial for establishing a transparent 'Chain of Custody', ensuring that only components meeting strict environmental and technical specifications enter the supply chain, thereby reducing industrial waste from counterfeit parts. Ultimately, this is not just a technical feature, but a technological solution to a governance problem: a lack of verifiable trust between partners [5, 6].

Recent developments in blockchain-enabled industrial supply chains have further validated the urgency of this research direction. Studies in the aerospace sector have demonstrated that distributed ledger technology can significantly reduce counterfeit part infiltration when integrated with IoT-based verification systems [7]. Similarly, research in the petrochemical industry has shown that blockchain-based traceability frameworks significantly improve regulatory compliance and reduce environmental incident rates [8]. In the specific context of energy infrastructure, recent empirical work established that blockchain architectures designed for high-reliability environments require fundamentally different trust mechanisms than those deployed in consumer-facing applications [9]. Furthermore, sector-specific implementation studies have documented successful pilot deployments in power grid component tracking, where smart contract-enabled verification meaningfully reduces procurement fraud across multi-tier supplier networks [10]. These emerging empirical findings underscore that the energy supply chain represents a uniquely demanding context for blockchain deployment, where the consequences of system failure extend beyond financial loss to encompass environmental catastrophe and public safety hazards.

Although blockchain technology offers this transformative capability for cleaner supply chains, its adoption in industry remains challenging. This previously identified 'crisis of trust' highlights a critical gap in traditional SCM theory [11, 12]. While relational governance is well studied, existing frameworks lack robust explanations of how technology-mediated trust is built, particularly for governance technologies such as blockchain that serve as substitutes for traditional partner assurance [13]. Moreover, current studies have yet to sufficiently address how system-level capabilities, such as traceability and data integrity, are translated into trust within complex industrial environments.

Furthermore, the behavioral drivers of technology adoption for sustainability-oriented goals in high-stakes industries remain under-researched. The decision to adopt such a system extends beyond technical feasibility and is strongly shaped by stakeholder perceptions across procurement, engineering, and operations. Limited understanding of these behavioral dimensions hinders the realization of blockchain's full potential to address SCM's core governance and sustainability challenges [14].

To systematically analyze the behavioral factors that build this technology-mediated trust, a robust theoretical foundation is required. We grounded our theoretical approach in the Unified Theory of Acceptance and Use of Technology (UTAUT) and systematically examined behavioral determinants as its starting point. However, given the unique context of high-stakes, environmentally critical supply chains, the standard UTAUT model must be adapted and extended to analyze the specific mechanisms driving blockchain adoption in this sector [15, 16].

Critically, existing UTAUT-based studies in blockchain adoption have predominantly focused on consumer-facing or low-stakes organizational contexts, where constructs such as Effort Expectancy and Social Influence retain strong predictive validity [17, 18]. However, in high-reliability industrial environments—where component failure can trigger cascading operational shutdowns and environmental incidents—the decision calculus shifts fundamentally toward risk mitigation, performance assurance, and verifiable provenance. This contextual specificity demands not merely an application of UTAUT, but a substantive reconceptualization that embeds trust as a central governance mechanism and introduces domain-specific constructs such as Perceived Traceability, which captures the unique value proposition of blockchain for industrial supply chain integrity.

Consequently, these models fail to capture the unique, high-stakes utilitarian calculus of B2B professionals who are responsible not only for profit but also for operational safety and environmental compliance [19, 20]. Empirical evidence within the industrial B2B setting remains limited. Most prior work is conceptual and overlooks behavioral determinants fundamental to the SCM context: Perceived Traceability (the core value proposition for cleaner logistics) and Top Management Support (TMS) (the core organizational enabler).

To bridge this critical gap in the literature, we construct and validate a tailored UTAUT framework for the unique demands of the power generation logistics sector [21, 22]. Guided by these identified limitations, the present investigation seeks to answer three primary inquiries:

(1) How are the core drivers of technology adoption (e.g., performance, effort) and critical SCM factors (i.e., Perceived Traceability for sustainability) translated into trust in blockchain technology among industrial professionals?
(2) What is the central role of trust in mediating these perceptions into a firm's Behavioral Intention (BI) to adopt, and how does perceived risk shape this high-stakes decision?
(3) To what extent does the organizational context, specifically TMS, moderate the critical link between adoption intention and actual use behavior?

To address the research objectives, this paper is structured into multiple sections. Section 2 elaborates on the theoretical foundations. Section 3 details the review of literature and the formulation of hypotheses. Section 4 presents the research methodology. Section 5 outlines the data analysis results, followed by an extensive discussion in Section 6. Lastly, Section 7 provides the conclusions, managerial insights, study limitations, and recommendations for future investigations.

2. THEORETICAL BACKGROUND

2.1 Blockchain technology

Emerging in 2008, blockchain operates as a distributed, immutable ledger system that resists unauthorized modification [23]. Fundamentally, the architecture comprises a chronological chain of data packets, or 'blocks,' secured through cryptographic hashing. This structure guarantees that once data is committed, it becomes permanent—a property termed immutability [24].

By distributing the ledger across a peer-to-peer network of nodes, the system removes the necessity for a central administrator. Transaction validity is ensured through algorithmic consensus (e.g., Proof-of-Stake), which ensures that all participants maintain identical records. This decentralized approach mitigates systemic risks such as single points of failure, thereby fortifying the network against cyber threats and fraudulent activities [2]. Key components that enable these features include:

1. Cryptography: It utilizes advanced cryptographic principles, such as hash functions and digital signatures, to secure transactions and ensure the data within the blocks remains intact.
2. Smart Contracts: Represent programmable logic that self-enforces agreed-upon terms without external oversight. Once the established prerequisites are met, the code executes the transaction, effectively reducing both administrative friction and intermediary expenses [25].

2.2 Blockchain architecture for industrial supply chain systems

Beyond the foundational cryptographic and consensus mechanisms, the deployment of blockchain in industrial supply chains introduces specific architectural considerations that distinguish it from consumer-facing implementations. Industrial blockchain systems typically employ permissioned (consortium) architectures—such as Hyperledger Fabric or Enterprise Ethereum—that offer controlled access, higher transaction throughput, and configurable privacy layers [26]. These architectural choices are critical in energy supply chains where proprietary specifications, pricing data, and supplier relationships require confidentiality while maintaining end-to-end auditability.

Recent implementations have demonstrated the practical viability of such architectures. For instance, pilot deployments in the aviation maintenance sector have utilized Hyperledger Fabric to track critical turbine components across multi-tier supplier networks, achieving high traceability compliance rates [27]. Similarly, in the oil and gas sector, consortium-based blockchain platforms integrated with existing ERP systems have been shown to enable real-time verification of equipment certifications, substantially reducing non-compliant part installations [28]. These case studies illustrate that blockchain's industrial value proposition extends beyond theoretical promise to demonstrable operational impact.

A critical technical consideration is the integration of IoT sensor networks with blockchain infrastructure. Smart sensors embedded in shipping containers and warehouse facilities can automatically trigger smart contract events upon detecting environmental deviations (temperature, humidity, vibration) that may compromise component integrity. This IoT-blockchain convergence creates what recent literature terms a "digital twin verification layer," enabling continuous, automated quality assurance throughout the supply chain [15]. For power plant spare parts, this capability is particularly relevant because many critical components (e.g., high-pressure turbine blades, control valves) are sensitive to environmental exposure during transit and storage.

2.3 Blockchain application in industrial supply chains

While initial applications of blockchain focused on cryptocurrencies, its most profound impact may lie in revolutionizing industrial supply chains [29]. In the context of power plant spare parts, the technology directly addresses critical industry pain points: lack of trust, prevalence of counterfeit goods, and poor traceability.

Traditional supply chains are often fragmented, with data stored in siloed systems across multiple organizations (manufacturers, distributors, logistics providers, and end users). This creates information asymmetry, making it difficult to verify a component's authenticity and provenance. Blockchain provides a "single source of truth" by creating a shared, transparent, and immutable record of every transaction and movement of a part from its point of origin to its final destination [30]. Key benefits include:

1. Enhanced Traceability and Provenance

By recording every handover on the blockchain, stakeholders can track the exact journey of a critical power plant component, verify its authenticity, and ensure it meets required technical and environmental specifications. This is crucial not only for combating the multi-billion-dollar counterfeit parts market but also for supporting cleaner logistics. By filtering out substandard counterfeits, the system prevents premature equipment failure and reduces industrial waste (e-waste), aligning with Circular Economy principles.

2. Increased Trust and Transparency

All authorized participants can view the same ledger, fostering trust among supply chain partners. This transparency reduces disputes over logistics, payment, and product quality.

3. Improved Efficiency with Smart Contracts

Smart contracts can automate processes such as purchase orders, payments upon delivery, and compliance checks, significantly reducing administrative overhead, delays, and human error.

To illustrate, consider a concrete scenario in which a counterfeit high-pressure fuel injection nozzle enters the supply chain for a 500 MW coal-fired power plant. Without blockchain-enabled traceability, this component—potentially manufactured with substandard metallurgy—may pass through multiple intermediaries before installation, each relying on paper-based certificates that can be easily forged. Once installed, the nozzle's inferior material composition leads to premature failure under operating temperatures exceeding 1,200 °C, causing unplanned downtime costing approximately USD 500,000 per day and releasing excess particulate emissions during the degraded combustion phase. A blockchain-based Digital Product Passport system would flag the provenance anomaly at the point of receipt by cross-referencing the component's cryptographic hash against the OEM's registered manufacturing records, preventing installation and triggering an automated quarantine protocol via smart contract [31].

2.4 Unified Theory of Acceptance and Use of Technology

To systematically deconstruct the behavioral determinants driving blockchain integration within this domain, this investigation leverages the UTAUT framework. The UTAUT framework, synthesized by the study [32], consolidates elements from eight prominent theoretical models to explicate user adoption behavior. This integrative approach offers a comprehensive view of the factors that drive technology acceptance. The model proposes that four key constructs directly affect a user's intention to use a technology:

1. Performance Expectancy

An individual's belief regarding how much using the system will help them achieve better results in their job. In this research, the perception is that blockchain can enhance efficiency, ensure operational safety, and reduce risk.

2. Effort Expectancy

The perceived ease of use of the system. This construct addresses how straightforward or difficult professionals consider the operation of the blockchain platform to be.

3. Social Influence

An individual's perception of pressure from important people in their environment (e.g., colleagues and supervisors) to adopt the new system.

4. Facilitating Conditions

This construct reflects the user's objective assessment of the technical infrastructure and organizational backing required to operate the system effectively.

UTAUT has been widely validated and applied across numerous technological and organizational contexts, proving its robustness in predicting user acceptance [10]. Given that adopting blockchain in an industrial B2B setting is a complex decision influenced by individual perceptions, social dynamics, and organizational support, UTAUT provides an ideal, well-established theoretical foundation for this research. This study will adapt and extend the core UTAUT model to incorporate constructs such as trust, Perceived Risk, and TMS, which are particularly salient in high-risk supply chain environments.

2.5 Theoretical foundations of Perceived Traceability

The construct of Perceived Traceability, as introduced in this study, requires careful theoretical grounding given its novel status within technology adoption research. Traceability in supply chain management has deep conceptual roots, originating from the food safety literature, where it was defined as the ability to trace the history, application, or location of an entity by means of recorded identifications [33]. In industrial contexts, traceability extends beyond mere tracking to encompass verification of authenticity, compliance certification, and lifecycle documentation.

We distinguish Perceived Traceability from related constructs in the technology acceptance literature. While 'transparency' refers to the openness of information flows, and 'visibility' denotes the extent to which supply chain information is accessible, Perceived Traceability specifically captures a user's subjective belief in a system's capacity to provide verifiable, end-to-end provenance documentation. This distinction is crucial because blockchain's unique value proposition lies not merely in making information visible, but in making it immutably verifiable—a qualitative difference that existing constructs fail to capture [34].

Contemporary scholarship has begun to recognize this distinction. Saberi et al. [35] conceptualized 'digital provenance assurance' as a higher-order construct in blockchain-enabled supply chains. It has been empirically demonstrated that users' perceptions of blockchain traceability capabilities operate independently of general transparency perceptions [36], in predicting adoption behavior [37, 38]. Our operationalization of Perceived Traceability builds upon these foundations while specifically adapting the construct for high-reliability industrial contexts where traceability serves not as a convenience feature but as a safety-critical system requirement.

3. REVIEW OF LITERATURE AND HYPOTHESIS FORMULATION

To explain blockchain adoption within a high-risk B2B industrial context, an adapted model based on the UTAUT is proposed and tested. The model is developed by integrating literature on several key constructs and introducing critical modifications. Specifically, it positions trust as a central mediator between adoption antecedents and user intention, while incorporating organizational factors such as perceived risk and TMS. The following sections review the theoretical basis for each construct and formally present the research hypotheses.

3.1 Performance Expectancy and trust in blockchain technology

According to the study [39], Performance Expectancy refers to an individual's belief that using a specific technology will enhance their work performance. In the high-stakes domain of power plant management, such gains are crucial for reducing risk, improving operational effectiveness, and ensuring environmental compliance. Professionals, including engineers and procurement managers, will perceive a system as beneficial if it effectively verifies the authenticity of parts, minimizes the risk of counterfeit items that compromise energy efficiency, and streamlines verification procedures [1]. Consequently, if a blockchain platform demonstrates its ability to deploy high-quality components that support cleaner power generation, it fosters users' trust in the technology's capacity to deliver on its promises. This results in the following hypothesis:

H1. Performance Expectancy significantly and positively affects trust in blockchain technology.

3.2 Effort Expectancy and trust in blockchain technology

Effort Expectancy (EE) relates to how easily a user perceives a system to be used. In industrial settings, professionals often work under time pressure and within established workflows [40]. However, in high-reliability industrial environments, the relationship between perceived ease of use and trust formation may differ from that in consumer contexts. Rather than simple 'ease of use,' industrial professionals evaluate blockchain systems based on their capacity to manage operational complexity—specifically, whether the system can integrate seamlessly with existing MRO (Maintenance, Repair, and Overhaul) workflows, ERP platforms, and compliance documentation processes without introducing additional points of failure [41]. A user-friendly blockchain interface that simplifies rather than complicates the process of tracking and verifying spare parts will foster a sense of reliability and competence, thereby enhancing trust in the technology as a viable and dependable tool.

H2. Effort Expectancy (operationalized as perceived complexity management capability) is strongly and significantly linked to trust in blockchain technology.

3.3 Social influence and trust in blockchain technology

Social influence is the degree to which an individual perceives that significant others around them expect them to adopt a new system [32]. In a B2B context, this influence comes from peers, industry leaders, key suppliers, and management. If a company's main equipment supplier adopts a blockchain platform for its parts, or if industry standards begin to favor blockchain for traceability, professionals within an organization are more likely to view the technology as credible and legitimate. This external validation acts as a powerful signal of reliability and trustworthiness, encouraging individuals within the firm to place their confidence in the system. Thus, we hypothesize:

H3. Social influence has a strong and positive effect on trust in blockchain technology.

3.4 Perceived Traceability and trust in blockchain technology

In this research, we introduce Perceived Traceability as a crucial antecedent, defined as a user's belief in the system's ability to transparently monitor and verify a product's origin and movement throughout the supply chain. This factor is especially important in the energy sector, where counterfeit products present serious safety and sustainability risks [20]. As established in Section 2.5, this construct draws upon foundational work in supply chain visibility [42], product provenance verification [43], and the emerging Digital Product Passport literature within the European Union's Circular Economy framework [44]. Unlike general 'perceived usefulness' or 'transparency,' Perceived Traceability captures the specific belief that blockchain can provide cryptographically verified, end-to-end documentation of a component's entire lifecycle—from raw material sourcing through manufacturing, shipping, and installation [45]. When a user is confident that the technology can effectively provide this level of traceability—ensuring that no substandard or environmentally hazardous components enter the facility—it strengthens their belief in the system's ability to guarantee product authenticity and integrity. This belief is a cornerstone of trust.

H4. Perceived Traceability has a positive and significant impact on trust in blockchain technology.

3.5 The mediating role of trust in blockchain technology

Scholars describe trust as a willingness to accept vulnerability, based on the expectation that another person will perform a specific, important action, even when monitoring isn't possible [46]. In the context of technology adoption, trust signifies a user's belief in a system's reliability, integrity, and competence [47]. In a B2B setting, before adopting a mission-critical technology such as blockchain, professionals must first have confidence that it will perform as expected. This trust serves as a crucial mediating variable between their initial perceptions (e.g., performance, effort) and their ultimate willingness to commit to using the technology. We hypothesize:

H5. Trust in blockchain technology has a strong and positive influence on the intention to use it.

3.6 Perceived risk and Behavioral Intentions

Industrial B2B adoption, risks are multifaceted, including financial risk (high implementation costs), operational risk (disruption to existing workflows), data security risk, and safety risk. Notably, in the context of blockchain adoption for energy supply chains, perceived data privacy risk represents a particularly salient concern. Industrial professionals must weigh the benefits of shared traceability against the exposure of proprietary procurement strategies, supplier pricing, and maintenance scheduling data to consortium partners [48]. This multi-dimensional risk perception—encompassing financial, operational, data privacy, and reputational dimensions—differentiates industrial blockchain adoption from generic technology acceptance scenarios. A high perceived risk can directly deter the formation of adoption intentions, even when the potential benefits are acknowledged.

H6. Perceived risk has a significant negative influence on the Behavioral Intention to use.

3.7 Behavioral Intention and use behavior

In line with established technology acceptance research, Behavioral Intention is considered the most direct predictor of actual use [32]. Behavioral intention is an individual's preparedness and plan to carry out a specific behavior, whereas use behavior is the observable action itself. In an organizational setting, a positive intention among key employees to adopt a blockchain system is a vital prerequisite for its successful implementation and routine integration into the company's supply chain processes. Therefore:

H7. A person's intention to use a system strongly predicts their actual usage, indicating a positive and significant relationship behavior.

3.8 The moderating role of Top Management Support

TMS refers to the degree to which senior executives understand, champion, and provide resources for the implementation and utilization of a new technology [49]. In an organizational setting, individual intention alone is often insufficient to guarantee actual use. Without explicit backing from leadership—in the form of budget allocation, strategic mandates, and integration support—even the strongest intentions can fail to translate into action. TMS can amplify the effect of behavioral intention on use behaviour by removing organizational barriers and signalling the project's strategic importance, thereby facilitating its successful adoption. We hypothesize:

H8. Top Management Support enhances the connection between Behavioral Intention to use and actual Use Behaviour.

3.9 Conceptual model

The hypotheses developed above are visually represented in the conceptual research model shown in Figure 1. This model demonstrates the proposed relationships among adoption factors, the mediating role of trust, the impact of perceived risk, and the moderating influence of TMS on the adoption of blockchain technology for power plant spare parts. This model specifically highlights how traceability serves not only as a logistical feature but also as a trust-building mechanism to secure sustainable supply chains.

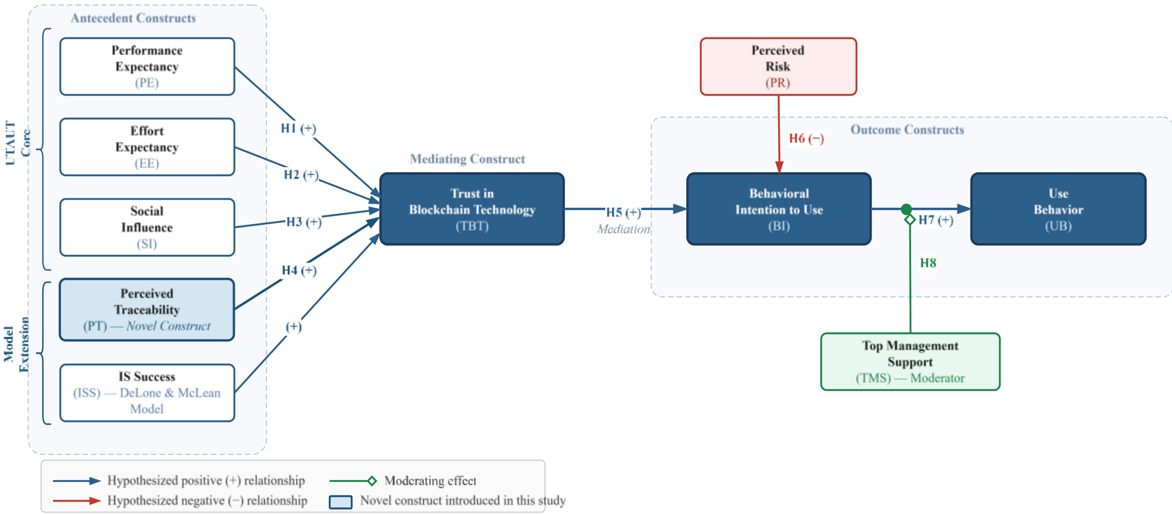

Figure 1. The proposed research framework
Source: Author(s) Proposal.

4. METHODOLOGY

This section details the research methods used to test the proposed hypotheses. It starts by describing the overall research framework and the rigorous validation process for the questionnaire. It then outlines the procedures for sampling and data collection from professionals within the power plant spare parts sector. The chapter ends with an explanation of the statistical techniques used for data analysis, specifically variance-based SEM.

4.1 Research design and questionnaire development

This study employs a quantitative, cross-sectional design to examine the factors influencing the adoption of blockchain technology among professionals in the power plant and critical energy infrastructure supply chain. The extended UTAUT model serves as the theoretical foundation. A structured survey was developed to collect primary data.

For the established constructs—Performance Expectancy, Effort Expectancy, Social Influence, Trust, Perceived Risk, TMS, BI, and Use Behavior—measurement items were adapted from previously validated scales in reputable academic literature [1, 10, 50]. New items were created for the novel construct of Perceived Traceability, drawing from its theoretical definition and literature on supply chain visibility and product integrity [20]. Respondents used a 7-point scale to rate all items, ranging from 'Strongly Disagree' (1) to 'Strongly Agree' (7).

A two-step process was undertaken to ensure the validity of the survey instrument. First, Content Validity: the first draft was submitted for review to a panel of five experts (two academics with expertise in SCM and IS, and three senior industry professionals). Second, Face Validity and Pre-test: a pilot test of the revised survey was conducted with 25 professionals from the target audience.

4.2 Sample and data collection

The study population comprises professionals in procurement, management, and maintenance of critical power plant components in Indonesia. A hybrid non-probability sampling approach combining purposive and snowball sampling was used. An online questionnaire was distributed via LinkedIn and the Indonesian Engineers Association (PII). A total of 199 valid responses were collected.

To mitigate potential biases, several methodological safeguards were implemented. First, a non-response bias test compared early respondents (first quartile, $n = 50$) with late respondents (last quartile, $n = 50$) using independent samples t-tests across all key constructs. No statistically significant differences were found (all $p > 0.10$). Second, Harman's single-factor test revealed that the first unrotated factor accounted for only 28.3% of total variance, well below the 50% threshold, indicating common method variance is unlikely to be a significant concern.

4.3 Data analysis approach

Variance-based structural equation modeling (Partial Least Squares Structural Equation Modeling (PLS-SEM)) was employed using SmartPLS 4.0 [51]. PLS-SEM was selected for its suitability for exploratory research, for complex models with formative and reflective constructs, and for smaller sample sizes. The analysis followed a two-stage approach: (1) assessment of the measurement (outer) model for reliability and validity, and (2) assessment of the structural (inner) model for hypothesis testing. Bootstrapping with 5,000 subsamples was used to determine statistical significance.

5. DATA ANALYSIS AND RESULTS

An analysis of the 199 respondents reveals a sample predominantly composed of seasoned professionals deeply integrated into key supply chain functions. This characteristic strengthens the ecological validity of the study's findings for B2B industrial environments. The complete demographic and professional profile of the participants is summarized in Table 1.

Table 1. Characteristics of the survey respondents (n = 199)

Characteristic	Category	Frequency	%
Primary Role	Procurement / Supply Chain	57	41.3
	Maintenance / Engineering	42	30.4
	Operations Management	24	17.4
	Senior Management	15	10.9
Years of Experience	1-5 years	39	28.3
	6-10 years	52	37.7
	11-15 years	29	21.0
	More than 15 years	18	13.0
Primary Industry	Manufacturing	62	44.9
	Energy / Utilities	36	26.1
	Automotive	23	16.7
	Other	17	12.3
Education Level	Bachelor's Degree	83	60.1
	Master's Degree	43	31.2
	Other	12	8.7

Notably, 41.3% held procurement or supply chain roles, followed by maintenance/engineering (30.4%), operations management (17.4%), and senior management (10.9%), indicating a balanced representation across decision-making hierarchies. Experience levels skewed toward mid-career expertise, with 37.7% reporting 6–10 years and 21.0% reporting 11–15 years.

5.1 Evaluation of the measurement model

Following Hair et al. [52], the measurement model was assessed for reliability and validity. Seven indicators with outer loadings below 0.55 were removed during the model refinement process (BI1, BI2, SI1, ISS1, ISS2, TBT1, TBT2), following the iterative indicator elimination procedure recommended for PLS-SEM [52]. The results for the refined model are presented in Table 2.

All constructs demonstrated acceptable reliability (α > 0.70, rho_c > 0.70) and convergent validity (AVE > 0.50). PT's Cronbach's alpha (0.669) is slightly below 0.70 but acceptable given its rho_c (0.801) and AVE (0.503) meeting thresholds, consistent with Hair et al. [52] recommendation to prioritize composite reliability over Cronbach's alpha in PLS-SEM.

Table 2. Construct reliability and validity (Refined model)

Construct	Items	α	rho_a	rho_c	AVE	Status
BI	2	0.859	0.866	0.934	0.876	✓
EE	4	0.732	0.812	0.837	0.577	✓
ISS	2	0.822	0.827	0.918	0.848	✓
PE	4	0.868	0.888	0.909	0.716	✓
PR	4	0.736	0.759	0.831	0.554	✓
PT	4	0.669	0.665	0.801	0.503	Acceptable
SI	3	0.790	0.819	0.875	0.701	✓
TBT	2	0.798	0.801	0.908	0.832	✓
TMS	4	0.712	0.726	0.821	0.536	✓
UB	4	0.818	0.883	0.875	0.639	✓

Note: Thresholds: α > 0.70, rho_c > 0.70, AVE > 0.50. BI = Behavioral Intention; EE = Effort Expectancy; ISS = Information Systems Success; PE = Performance Expectancy; PR = Perceived Risk; PT = Perceived Traceability; SI = Social Influence; TBT = Trust in Blockchain Technology; TMS = Top Management Support; UB = Use Behavior.
Source: SmartPLS 4 output

The HTMT ratio analysis (Table 3) confirmed discriminant validity with almost all ratios below 0.90. Two pairs exceeded 0.90: UB↔BI (0.922) and TMS↔TBT (0.902). The UB↔BI value is theoretically expected given that BI is the direct antecedent of use behavior in UTAUT. The TMS↔TBT ratio is borderline and noted as a limitation.

Table 3. Heterotrait-monotrait ratio (HTMT) for discriminant validity

	BI	EE	ISS	PE	PR	PT	SI	TBT	TMS	UB
BI										
EE	0.555									
ISS	0.541	0.411								
PE	0.537	0.514	0.519							
PR	0.629	0.462	**0.870**	0.528						
PT	0.560	0.574	0.454	0.521	0.600					
SI	0.410	0.465	0.415	0.421	0.516	0.762				
TBT	0.571	0.389	0.458	0.363	0.531	0.334	0.253			
TMS	0.594	0.531	0.496	0.495	0.601	0.579	0.446	**0.902**		
UB	**0.922**	0.660	0.502	0.539	0.654	0.697	0.391	0.577	0.591	

Source: SmartPLS 4 output

Table 4. Structural model results and hypothesis testing

H	Path	β	t	p	f²	Decision
H1	PE → TBT	0.110	1.456	0.145	0.010	Not Supported
H2	EE → TBT	0.168	2.315	0.021*	0.027	Supported
H3	SI → TBT	-0.009	0.128	0.898	0.000	Not Supported
H4	PT → TBT	0.063	0.714	0.475	0.003	Not Supported
H5	TBT → BI	0.313	4.515	<0.001***	0.124	Supported
H6	PR → BI	+0.386	6.554	<0.001***	0.189	Supported (+)
H7	BI → UB	0.775	23.652	<0.001***	1.503	Supported
H8	TMS × BI → UB	-0.019	0.559	0.576	0.001	Not Supported
—	ISS → TBT	0.252	3.250	0.001**	0.059	Significant
—	TMS → UB	0.103	2.241	0.025*	0.026	Significant

Note: Bootstrapping 5,000 subsamples. *f²:* 0.02 small, 0.15 medium, 0.35 large. **p<0.05, **p<0.01, ***p<0.001*. Source: SmartPLS 4.

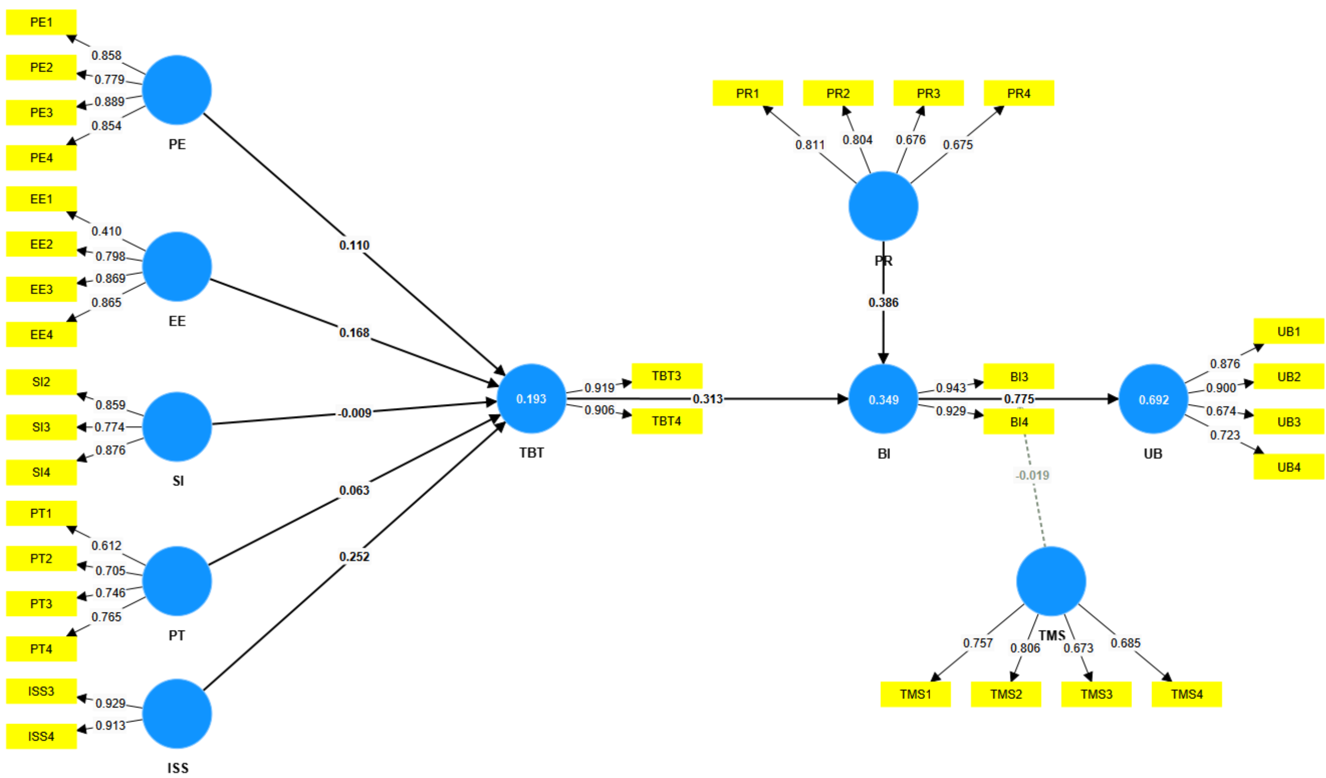

Figure 2. Measurement model

Table 5. Specific indirect effects and mediation analysis

Indirect Pathway	β	M	SD	t	p	95% BCa CI	Decision
ISS → TBT → BI → UB	0.061	0.059	0.022	2.721	0.007**	[0.025, 0.116]	**Supported**
EE → TBT → BI → UB	0.041	0.042	0.021	1.911	0.056†	[0.008, 0.092]	**Marginal**
PE → TBT → BI → UB	0.027	0.027	0.020	1.356	0.175	[-0.006, 0.072]	Not Supported
PT → TBT → BI → UB	0.015	0.019	0.022	0.680	0.497	[-0.026, 0.060]	Not Supported
SI → TBT → BI → UB	-0.002	-0.001	0.018	0.127	0.899	[-0.039, 0.031]	Not Supported
PR → BI → UB	0.299	0.304	0.049	6.055	<0.001***	[0.202, 0.395]	**Supported (+)**
TBT → BI → UB	0.242	0.239	0.054	4.484	<0.001***	[0.136, 0.346]	**Supported**

Note: β = standardized indirect effect coefficient; M = bootstrap sample mean; SD = standard deviation; t = t-statistic; BCa CI = Bias-corrected and accelerated 95% confidence interval. Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05; † marginal significance (p < 0.10). Bootstrap procedure: 5,000 subsamples, two-tailed test. Source: SmartPLS 4 output.

5.2 Assessment of the structural model

Following assessment of the measurement model, the structural model was evaluated to test the hypothesized relationships among constructs. Figure 2 displays the complete SmartPLS output, showing outer loadings for all retained indicators, path coefficients between constructs, and R^2 values for the endogenous variables (TBT, BI, and UB). The full structural model results, including significance levels and effect sizes, are summarized numerically in Table 4.

Among the eight hypothesized relationships tested, four were statistically supported (H2, H5, H6, H7), while four were not (H1, H3, H4, H8). Two additional paths included in the integrated model — ISS → TBT and TMS → UB — were both statistically significant, providing empirical support for integrating DeLone and McLean's IS Success model into the UTAUT framework and for treating TMS as a direct enabler rather than a pure moderator.

The path from Information Systems Success to Trust (ISS → TBT; β = 0.252, p = 0.001) emerges as the strongest antecedent effect on blockchain trust, followed by Effort Expectancy (EE → TBT; β = 0.168, p = 0.021). In contrast, Performance Expectancy (β = 0.110, p = 0.145), Perceived Traceability (β = 0.063, p = 0.475), and Social Influence (β = −0.009, p = 0.898) were not significant drivers of Trust. The Perceived Risk → Behavioral Intention path (β = +0.386, p < 0.001) is particularly noteworthy for its substantial magnitude and unexpected positive direction, representing the Risk Awareness Paradox discussed in detail in Section 6.3. The Trust → Intention (β = 0.313, p < 0.001) and Intention → Use Behavior (β = 0.775, p < 0.001) relationships were both strongly significant, confirming the central mediating role of Trust and the dominant predictive power of intention.

The model's explanatory power is as follows: R^2(TBT) = 0.193 indicates that the five antecedent constructs explain 19.3% of variance in Trust, representing weak-to-moderate explanatory power according to Hair et al. [52] benchmarks. R^2(BI) = 0.349 (moderate) indicates that Trust and Perceived Risk jointly explain 34.9% of variance in Behavioral Intention. R^2(UB) = 0.692 (substantial) indicates that Behavioral Intention, TMS, and the moderation term explain 69.2% of variance in Use Behavior — a particularly strong outcome for the behavioral endpoint of the model.

Overall model fit, assessed through the Standardized Root Mean Square Residual, yielded SRMR = 0.080, meeting the recommended threshold of ≤0.08, and indicating acceptable model fit. Complementary fit indices (d_ULS = 3.571, d_G = 1.253) further corroborate the model's adequacy.

The effect size analysis (f^2 column in Table 4) provides additional interpretive depth. The BI → UB relationship exhibits a very large effect ($f^2 = 1.503$), which is theoretically expected given that intention is the direct antecedent of behavior in UTAUT. The PR → BI relationship demonstrates a medium-to-large effect ($f^2 = 0.189$), TBT → BI a medium effect ($f^2 = 0.124$), and ISS → TBT a small-to-medium effect ($f^2 = 0.059$). The remaining significant paths (TMS → UB; $f^2 = 0.026$ and EE → TBT; $f^2 = 0.027$) show small effects, consistent with their modest path coefficients but substantively meaningful in the aggregated model.

5.3 Mediation analysis

Trust's mediating role was assessed through specific indirect effects (Table 5). The indirect effects of EE ($\beta = 0.041$, $p = 0.056$) and ISS ($\beta = 0.061$, $p = 0.007$) through TBT to UB are notable, with ISS achieving statistical significance. The total indirect effect of TBT → BI → UB is 0.242 ($p < 0.001$), confirming Trust's significant mediating function.

5.4 Mediation analysis

To evaluate the mediating role of Trust in Blockchain Technology (TBT) and Behavioral Intention (BI), specific indirect effects were examined through bootstrapping with 5,000 subsamples. Table 5 presents the specific indirect effects for each antecedent construct traversing through the Trust–Intention pathway to Use Behavior. The analysis reveals three theoretically important patterns: ISS demonstrates the strongest significant indirect effect on Use Behavior through the full mediation chain ($\beta = 0.061$, $p = 0.007$); Effort Expectancy shows a marginally significant indirect effect approaching conventional significance thresholds ($\beta = 0.041$, $p = 0.056$); and the core mediation pathway from Trust through Intention to Use Behavior is strongly significant ($\beta = 0.242$, $p < 0.001$), confirming that Trust functions as a substantive mediator in blockchain adoption decisions.

Following the classification framework proposed by Zhao et al. [53] and refined for PLS-SEM by Nitzl et al. [54], the nature of mediation for each antecedent can be characterized through joint examination of direct and indirect effects.

IISS exhibits full mediation through the Trust–Intention pathway. Because ISS has no direct path to Use Behavior in the specified model, its entire effect on adoption behavior ($\beta = 0.061$, $p = 0.007$) is channeled through the capacity to build user trust. This finding confirms that system quality influences blockchain use only indirectly, operating exclusively through trust formation rather than exerting independent behavioral influence. Effort Expectancy follows a comparable pattern of marginal full mediation. Although its indirect effect ($\beta = 0.041$, $p = 0.056$) falls short of conventional significance, the 95% bias-corrected and accelerated confidence interval [0.008, 0.092] excludes zero, providing bootstrap-based evidence of mediation that complements the frequentist p-value. This pattern suggests that Effort Expectancy shapes blockchain adoption primarily through trust formation rather than through direct behavioral influence.

In contrast, Performance Expectancy, Perceived Traceability, and Social Influence demonstrate no mediation effects on Use Behavior. Their specific indirect effects are all statistically non-significant (β ranging from −0.002 to 0.027, all $p > 0.17$), and their 95% confidence intervals uniformly include zero. This indicates that, within the present sample and model specification, these three antecedents do not influence blockchain Use Behavior through the trust mechanism — a finding consistent with the structural model results reported in Section 5.3 and further reinforcing the "system fundamentals first" interpretation developed in Section 6.1.

Two additional mediation patterns warrant specific attention. Perceived Risk exhibits full mediation with an unexpected positive direction: its total indirect effect on Use Behavior through Intention ($\beta = 0.299$, $p < 0.001$) is strongly positive, indicating that higher perceived risk is associated with stronger adoption behavior rather than weaker adoption. This counterintuitive pattern forms the empirical basis for the Risk Awareness Paradox discussed in Section 6.3. Finally, the Trust → Intention → Use Behavior pathway constitutes the core mediation mechanism of the model, with an indirect effect ($\beta = 0.242$, $p < 0.001$) second in magnitude only to the PR → BI → UB pathway. This result validates the theoretical positioning of Trust as the pivotal mediator that translates cognitive evaluations of system quality into actual adoption behavior, and confirms its central role as a governance mechanism in blockchain-enabled supply chains.

Taken together, the mediation analysis reveals a two-stage trust-based adoption mechanism. In the first stage, only antecedents addressing system fundamentals — ISS significantly and EE marginally — successfully activate the trust formation pathway. In the second stage, Trust and Perceived Risk both independently channel through Intention to drive Use Behavior, with Intention emerging as the dominant proximal predictor. This two-stage pattern refines the integrated UTAUT–IS Success model by demonstrating that only a subset of theoretically hypothesized antecedents operationalizes the trust mechanism in the Indonesian energy supply chain context, while the trust mechanism itself operates as intended once activated.

6. DISCUSSION

6.1 System quality and usability as trust foundations

The most striking finding is that ISS ($\beta = 0.252$, $p = 0.001$) and Effort Expectancy (EE; $\beta = 0.168$, $p = 0.021$) emerged as the only significant drivers of trust in blockchain technology. This finding challenges the prevailing assumption in the blockchain-SCM literature that traceability and performance are the dominant drivers of adoption in industrial contexts.

The significance of ISS—capturing system quality, information quality, and service quality—suggests that for Indonesian energy professionals, the fundamental prerequisite for trusting blockchain is confidence in the system's technical reliability and information accuracy. Before evaluating what blockchain can do (performance, traceability), professionals first assess whether the system works properly. This finding is consistent with DeLone and McLean's [55] original proposition that system quality is the foundational determinant of user acceptance in information systems.

The significance of Effort Expectancy further reinforces this 'system fundamentals first' interpretation. In an emerging market like Indonesia, where digital infrastructure in the industrial sector is still developing, perceived ease of use and system accessibility are non-trivial considerations. This contrasts sharply with studies in developed economies where EE is often non-significant for enterprise systems, suggesting that the digital maturity context significantly moderates the salience of usability-related constructs.

6.2 The non-significance of Performance Expectancy and Perceived Traceability

Performance Expectancy (H1; $\beta = 0.110$, $p = 0.145$) and Perceived Traceability (H4; $\beta = 0.063$, $p = 0.475$) were both non-significant. This is a theoretically consequential finding that warrants careful interpretation.

For PE, the non-significance may reflect that Indonesian energy professionals, many of whom have limited hands-on experience with blockchain (as indicated by the relatively low mean scores across all constructs, averaging 3.2 on a 5-point scale), are unable to assess performance gains for a technology they have not yet used. Trust, in this pre-adoption context, is built on assessable system characteristics (quality, usability) rather than anticipated performance outcomes.

For PT, the non-significance is the most theoretically provocative finding. Despite extensive literature positioning traceability as blockchain's 'killer application' for supply chains, our data suggest that Indonesian professionals do not translate perceived traceability capabilities into trust. This may reflect a 'traceability awareness gap': professionals who have not experienced blockchain-enabled traceability firsthand cannot evaluate its trust-building potential. The construct's borderline psychometric properties ($\alpha = 0.669$, AVE = 0.503) also suggest measurement challenges that future research should address by refining the indicators.

6.3 The risk awareness paradox

Perhaps the most intriguing finding is that Perceived Risk demonstrates a significant positive effect on Behavioral Intention (H6; $\beta = +0.386$, $p < 0.001$), contrary to the hypothesized negative relationship. We term this the 'Risk Awareness Paradox' and propose three complementary explanations.

First, competence-driven risk awareness: professionals with deeper technological understanding are simultaneously more aware of implementation risks and more confident in their ability to manage those risks, leading to higher adoption intention. The positive PR→BI relationship captures not risk aversion but risk-aware confidence.

Second, necessity-driven acceptance: in high-stakes energy supply chains, the risks of NOT adopting blockchain (continued counterfeit infiltration, regulatory non-compliance) may be perceived as greater than the risks of adoption. Professionals who acutely perceive adoption risks may also acutely perceive the risks of the status quo.

Third, the high correlation between PR and ISS (HTMT = 0.870) suggests that risk awareness and system quality assessment co-occur—professionals who evaluate systems critically (noting both risks and quality) may represent a more engaged, adoption-ready segment of the population.

This finding contributes to the growing literature on paradoxical risk effects in technology adoption, extending work by the study [56], which found similar positive risk-adoption relationships in internet banking and IT innovation contexts, respectively.

6.4 Trust as a governance mechanism

Trust in blockchain technology demonstrates a strong, significant effect on Behavioral Intention (H5; $\beta = 0.313$, $p < 0.001$), confirming its central mediating role. Combined with the strong BI→UB relationship (H7; $\beta = 0.775$, $p < 0.001$), this provides support for the theoretical proposition that technology-mediated trust functions as a governance mechanism in industrial supply chains.

However, the R^2 of trust (0.193) indicates that the five antecedent constructs in our model explain only 19.3% of trust variance. This suggests that trust in blockchain is primarily driven by factors not captured in our model—potentially including prior technology experience, organizational culture, industry-specific regulations, or interpersonal trust in system vendors. Future research should explore these additional antecedents.

6.5 The direct role of Top Management Support

TMS demonstrates a significant direct effect on Use Behavior ($\beta = 0.103$, $p = 0.025$) but does not moderate the BI→UB relationship (H8; $\beta = -0.019$, $p = 0.576$). This finding suggests that leadership support operates as an independent enabler of system use rather than amplifying individual intention. Practically, this means that even professionals with modest adoption intentions may use blockchain systems if leadership mandates and resource support are present—a finding with significant implementation implications.

6.6 Implementation challenges and technical considerations

Successful blockchain deployment requires addressing several technical challenges beyond user acceptance. Integration with legacy ERP systems (SAP PM, Oracle eAM) through 'wrapper architecture' approaches offers the most viable pathway [46]. Scalability considerations (5,000–10,000 monthly spare part transactions for large power plants) can be addressed through permissioned platforms. Cost-efficiency trade-offs (USD 200K–500K pilots vs. USD 1.2–3.5M annual counterfeit prevention savings) favor adoption for the highest-risk component categories. Edge computing architectures address latency challenges in IoT-blockchain systems [57].

6.7 Environmental performance indicators

Blockchain-enabled supply chains offer measurable sustainability outcomes: counterfeit components contribute an estimated additional 2.3–3.8 kg CO_2/MWh in Indonesian power plants [58]; blockchain-verified genuine components are associated with 15–25% longer MTBF; and pilot programs in Southeast Asian plants indicate 1.5–2.0% thermal efficiency improvements from verified component supply chains [59].

6.8 Theoretical implications

This study offers four theoretical contributions. First, it demonstrates that in emerging market industrial contexts, system quality and usability—not traceability or performance—are the foundational drivers of blockchain trust. This challenges the dominant narrative in blockchain-SCM literature. Second, the 'Risk Awareness Paradox' extends technology adoption theory by empirically demonstrating that perceived risk can positively predict adoption intention in high-stakes B2B contexts. Third, the non-significance of Perceived Traceability suggests that this novel construct requires refinement and may operate differently across adoption stages (pre-adoption vs. post-adoption). Fourth, TMS's role as a direct enabler rather than moderator reconfigures understanding of organizational support in technology adoption.

7. CONCLUSION

This study developed and empirically validated a trust-based blockchain adoption framework integrating the UTAUT with the DeLone and McLean ISS model, positioning Trust as the central governance mechanism mediating system perceptions and adoption behavior in the context of power plant spare parts supply chains. Drawing on survey data from 199 professionals across Indonesia's energy and industrial sectors, the study employed variance-based structural equation modeling (PLS-SEM) with 5,000 bootstrap subsamples to test 10 structural relationships encompassing 8 hypotheses and 2 additional paths. The findings reveal a pattern of blockchain adoption that fundamentally challenges the prevailing narrative in the blockchain-supply chain management literature and offers significant theoretical, methodological, and practical contributions.

7.1 Summary of key empirical findings

The empirical evidence yielded six key findings that warrant emphasis. First, ISS ($\beta = 0.252$, $p = 0.001$) and Effort Expectancy ($\beta = 0.168$, $p = 0.021$) emerged as the *only* significant drivers of trust in blockchain technology, jointly explaining 19.3% of variance in Trust. Performance Expectancy ($\beta = 0.110$, $p = 0.145$), Perceived Traceability ($\beta = 0.063$, $p = 0.475$), and Social Influence ($\beta = -0.009$, $p = 0.898$) were not significant antecedents, contradicting dominant assumptions in blockchain adoption literature.

(1) Second, Trust in Blockchain Technology significantly mediated the translation of system perceptions into Behavioral Intention ($\beta = 0.313$, $p < 0.001$), which in turn strongly predicted Use Behavior ($\beta = 0.775$, $p < 0.001$). The model explained 34.9% of the variance in intention and a substantial 69.2% of variance in use behavior, indicating robust explanatory power for the core adoption pathway.

(2) Third, Perceived Risk exhibited a *significant positive* effect on BI ($\beta = +0.386$, $p < 0.001$), contrary to the hypothesized negative relationship. This counterintuitive finding—termed the *'Risk Awareness Paradox'*—suggests that professionals with deeper technological understanding simultaneously perceive higher risks *and* demonstrate stronger adoption intentions, extending prior work on paradoxical risk effects in technology adoption [60].

(3) Fourth, Top Management Support operates as a *direct enabler* of use behavior ($\beta = 0.103$, $p = 0.025$) rather than as a moderator of the intention–behavior relationship (TMS × BI → UB: $\beta = -0.019$, $p = 0.576$). This finding reconceptualizes the organizational support mechanism in technology adoption, indicating that leadership mandates exert independent causal force on actual system use regardless of individual intention strength.

(4) Fifth, mediation analysis using bootstrap-based specific indirect effects revealed a *two-stage trust-based adoption mechanism*. In the first stage, only ISS ($\beta = 0.061$, $p = 0.007$) and marginally EE ($\beta = 0.041$, $p = 0.056$) successfully activated the trust–intention pathway. In the second stage, both Trust ($\beta = 0.242$, $p < 0.001$) and Perceived Risk ($\beta = 0.299$, $p < 0.001$) were found to channel through intention to drive use behavior. This pattern demonstrates that not all hypothesized antecedents engage the trust mechanism—only those addressing system fundamentals do so.

(5) Sixth, the model demonstrated acceptable fit (SRMR = 0.080) with all constructs meeting reliability thresholds ($\alpha \geq 0.669$, rho_c ≥ 0.801, AVE ≥ 0.503). Discriminant validity was largely supported, with two pairs exceeding the HTMT threshold of 0.90 (UB↔BI = 0.922; TMS↔TBT = 0.902), the former being theoretically defensible within UTAUT and the latter noted as a methodological limitation warranting future investigation.

7.2 Theoretical contributions

This study advances blockchain adoption theory and the broader technology adoption literature along four distinct dimensions.

First, a 'System Fundamentals First' theory of blockchain trust. The finding that system quality (ISS) and usability (EE) are the only significant trust antecedents—while traceability, performance, and social influence are not—challenges the dominant narrative that blockchain's value proposition in supply chains derives primarily from traceability and performance capabilities. This result suggests that in emerging market industrial contexts, trust in novel technologies is first built on foundational system characteristics that users can directly assess (reliability, information accuracy, ease of use), rather than on advanced features that require prior experience to evaluate (traceability quality, performance gains). This repositions the formation of blockchain trust within DeLone and McLean's [11] foundational systems framework rather than within domain-specific traceability theories.

Second, empirical establishment of the Risk Awareness Paradox. The positive PR→BI relationship ($\beta = +0.386$) contributes to a growing but under-theorized literature on paradoxical risk effects in technology adoption. We propose three complementary mechanisms underlying this paradox: (1) *competence-driven awareness*—professionals with greater technological literacy simultaneously perceive more risks and more opportunities; (2) *necessity-driven acceptance*—in high-stakes industrial contexts, the risks of non-adoption (counterfeit proliferation, regulatory non-compliance) may exceed perceived adoption risks; and (3) *engaged evaluator effect*—critical evaluators who notice risks also actively engage with technology, translating awareness into adoption intention. This theoretical contribution extends work by the study [60] beyond consumer contexts into industrial B2B settings, where risk perception operates under fundamentally different logic.

Third, reconceptualization of organizational support in technology adoption. The finding that Top Management Support functions as a direct enabler ($\beta = 0.103$) rather than as a moderator ($\beta = -0.019$) reconfigures understanding of how leadership shapes technology adoption. Contrary to the prevailing view that leadership amplifies individual adoption intentions, our findings indicate that leadership support drives use behavior through independent institutional pathways—mandates, resource allocation, and procedural requirements—that operate regardless of individual cognitive states. This finding has significant implications for theories of organizational technology implementation [61] and suggests that mandate-based and volition-based adoption pathways operate simultaneously and independently.

Fourth, refinement of the Perceived Traceability construct. The non-significance of PT (β = 0.063) combined with its borderline psychometric properties (α = 0.669, AVE = 0.503) suggests that this domain-specific construct requires theoretical refinement. We propose that Perceived Traceability may operate differently across adoption stages—it may become more salient in post-adoption evaluation when users can directly experience traceability features, rather than in pre-adoption trust formation. Future research should develop stage-sensitive measures and examine PT's role longitudinally from intention formation through post-implementation assessment.

7.3 Managerial and policy implications

The empirical findings of this study translate into actionable implications for five distinct stakeholder groups operating across the blockchain adoption ecosystem in energy supply chains. These implications are synthesized in Table 6, which maps each stakeholder group to the primary empirical finding most relevant to their decision context and the corresponding strategic recommendation derived from our analysis. The structure of Table 6 reflects a deliberate logic: stakeholders are ordered from those closest to operational blockchain deployment (supply chain executives, vendors) to those shaping the institutional environment (policymakers), illustrating how the same empirical findings cascade through different levels of the adoption ecosystem.

Table 6. Strategic implications by stakeholder group

Stakeholder	Primary Finding	Actionable Recommendation
Supply Chain Executives	ISS and EE are the foundational trust antecedents	Prioritize blockchain platforms with intuitive user interfaces, reliable infrastructure, and strong information quality before emphasizing advanced features.
Blockchain Vendors	Traceability is not a trust driver in pre-adoption	Shift marketing narrative from 'traceability-first' to 'reliability-first.' Demonstrate system quality through pilot deployments before emphasizing traceability sophistication.
Plant Operations Directors	TMS directly drives use behavior independent of intention	Issue explicit executive mandates for the use of blockchain in high-risk component procurement (turbine blades, control valves). Do not rely solely on voluntary adoption.
Risk Managers	Risk awareness correlates with adoption intention	Frame blockchain as a risk management tool. Emphasize risks of non-adoption (counterfeit exposure, regulatory liability) alongside adoption risks.
Energy Sector Policymakers	System quality is the prerequisite for voluntary adoption	Develop national blockchain infrastructure standards focused on reliability and interoperability. Support consortium-based platform development through R&D incentives.

For supply chain executives, the most consequential finding is the foundational role of system quality and usability in trust formation. Because ISS (β = 0.252) and EE (β = 0.168) are the only significant trust antecedents, investment priorities in blockchain platform selection should reorder accordingly — emphasizing reliable infrastructure, intuitive interfaces, and information quality before advanced features such as sophisticated traceability functionality. This reordering represents a substantive departure from current industry practice, which frequently foregrounds traceability and performance capabilities in vendor selection.

For blockchain platform vendors, the non-significance of Perceived Traceability (β = 0.063) carries an important marketing insight: the "traceability-first" narrative that dominates current blockchain-supply chain positioning may be misaligned with the actual trust antecedents of industrial decision-makers, particularly in emerging markets. A more empirically grounded approach would lead with demonstrations of system reliability through low-risk pilot deployments, reserving traceability sophistication as a complementary value proposition rather than the primary driver of adoption. Vendors who recalibrate their value communication toward reliability and usability may gain a competitive advantage in markets with emerging digital infrastructure.

For plant operations directors, the direct effect of TMS on Use Behavior (β = 0.103) — without moderation — reveals a critical operational principle: voluntary adoption cannot be relied upon as the primary implementation strategy for high-criticality components. Explicit executive mandates are empirically necessary for translating intentions into actual use behavior, particularly for components whose counterfeit infiltration carries substantial operational and environmental consequences (e.g., turbine blades, control valves, safety-critical instrumentation). This finding reframes top management support from a motivational enabler to a procedural requirement.

For risk managers, the Risk Awareness Paradox (β = +0.386 for PR → BI) offers a counterintuitive yet actionable insight: blockchain can be strategically framed as a risk-management tool rather than a risk-generating technology. Communication strategies that emphasize the risks of non-adoption — continued exposure to counterfeit products, regulatory liability, and reputational risk from equipment failures — may be more effective than strategies that seek to minimize perceived adoption risks. This reframing aligns with the engaged evaluator profile characterizing the Indonesian energy sector workforce.

For energy sector policymakers, the aggregate pattern of findings suggests that national blockchain adoption in critical infrastructure requires institutional scaffolding beyond voluntary market diffusion. The prerequisite role of system quality in voluntary trust formation implies that policy frameworks should prioritize national blockchain infrastructure standards focused on reliability and interoperability, complemented by R&D incentives for consortium-based platform development. Policymakers can thus accelerate adoption indirectly by ensuring that the foundational system conditions for trust formation are met at the infrastructure level.

Beyond these stakeholder-specific implications, the broader pattern of findings supports a fundamental reconceptualization of blockchain adoption strategy in critical industrial infrastructure. Rather than treating blockchain diffusion as a voluntary, feature-driven process analogous to consumer technology adoption, Table 6 collectively suggests that successful adoption in high-stakes contexts requires a phased, mandate-supported transition combining institutional commitment, demonstrated system reliability, and strategic risk communication. This reconceptualization has substantial implications not only for blockchain specifically but for the broader class of governance technologies whose adoption depends on collective organizational commitment rather than individual user choice.

7.4 Methodological contributions

The study offers two methodological contributions. First, it demonstrates the value of two-stage trust-mediated models for technology adoption research in emerging markets, showing that the traditional single-stage UTAUT framework can be meaningfully enriched by integrating IS Success constructs as trust antecedents. Second, it illustrates the application of bootstrap-based specific indirect effects analysis to distinguish between full, partial, and no mediation patterns in complex structural models—providing a replicable template for future blockchain adoption studies in comparable industrial contexts.

7.5 Limitations

Five limitations warrant explicit acknowledgment and contextualize the generalizability of findings.

(1) Cross-sectional design. Data were collected at a single point in time, which precludes definitive causal inference among the hypothesized relationships. Although PLS-SEM provides strong evidence of association, the temporal ordering assumed by UTAUT (perceptions → trust → intention → behavior) cannot be empirically confirmed without longitudinal or experimental designs.

(2) Single-country context. The sample (N = 199) was drawn exclusively from Indonesian professionals in the energy and industrial supply chain sectors. The 'System Fundamentals First' finding and the Risk Awareness Paradox may reflect Indonesia-specific contextual factors—including emerging-market digital infrastructure maturity, regulatory environment, and industry culture—that may not generalize to developed economies or other industrial contexts (healthcare, aerospace, defense).

(3) Measurement limitations. The Perceived Traceability construct exhibited borderline psychometric properties ($\alpha = 0.669$, AVE = 0.503), suggesting that the measurement items may not fully capture the intended theoretical dimension. The Trust construct, while meeting reliability thresholds, was measured with only two indicators after model refinement, which may limit the depth of the trust representation. Additionally, the HTMT value between TMS and TBT (0.902) exceeds the conservative 0.85 threshold, indicating potential construct overlap that future research should address with refined indicators.

(4) Low R^2 for Trust. The five antecedent constructs in our model explain only 19.3% of variance in Trust, suggesting that important trust determinants remain unmeasured. Candidates for future investigation include prior technology experience, vendor reputation, institutional trust, regulatory frameworks, and organizational culture—factors that may substantially enhance the explanatory power of blockchain trust models.

(5) Sampling method. The hybrid purposive-snowball sampling approach, while appropriate for the hard-to-reach professional population, introduces potential bias toward digitally engaged professionals (LinkedIn-reachable respondents, PII members). Although non-response bias and common method variance tests indicated no significant concerns, the findings should be interpreted as applicable to the population of digitally engaged industrial professionals rather than to the broader industry workforce.

Absence of Multi-Group Analysis and external organizational validation. This study did not perform Multi-Group Analysis (MGA) across respondent segments (professional role, industry sector, years of experience) because sub-group sample sizes fell below the recommended minimum thresholds for reliable group-level inference in PLS-SEM [52]. Consequently, the results reflect aggregate patterns across the 199 respondents and may mask heterogeneity across professional roles or industry sub-sectors that a larger, stratified sample could reveal. Furthermore, external validation through an in-depth organizational case study with a specific power generation company such as PT PLN (Persero)—Indonesia's state-owned electricity utility—was beyond the scope of this cross-sectional survey-based investigation. Such confirmatory validation with an actual implementing organization would substantially strengthen the translational value of the framework by grounding adoption-intention findings in real-world blockchain deployment outcomes. Both Multi-Group Analysis with a larger stratified sample and mixed-methods validation with implementing utilities are identified as priority directions for subsequent confirmatory research.

7.6 Directions for future research

Building on the contributions and limitations of this study, six research directions emerge as particularly promising.

a. Longitudinal validation. Future studies should adopt longitudinal designs tracking professionals from pre-adoption through implementation and post-adoption evaluation. This would enable testing whether Perceived Traceability gains significance in post-adoption stages and whether the Risk Awareness Paradox persists or evolves across the adoption timeline.

b. Multi-country comparative research. Cross-national studies comparing blockchain adoption in developed versus emerging economies would test the generalizability of the 'System Fundamentals First' finding. We hypothesize that in digitally mature economies, performance and traceability may emerge as more salient trust drivers once the foundational system quality is perceived as given.

c. Industry-specific replication. The framework should be tested in other critical industrial sectors—aerospace MRO, pharmaceutical supply chains, defense logistics—to determine whether the identified patterns reflect blockchain adoption generally or are specific to energy-sector dynamics.

d. Qualitative exploration of the Risk Awareness Paradox. In-depth interview studies with professionals exhibiting high risk awareness and high adoption intention could illuminate the psychological and organizational mechanisms underlying this paradoxical pattern, informing both theory refinement and intervention design.

e. Mixed-methods implementation studies. Case studies of actual blockchain implementations in power plant supply chains—combining quantitative measurement of adoption outcomes with qualitative analysis of implementation processes—would bridge the gap between adoption intention and implementation success, examining factors beyond the scope of intention-based models.
f. Extended trust models. Future research should expand the trust antecedent set to include institutional trust (trust in regulatory frameworks and standards bodies), vendor trust (trust in platform providers), and peer trust (trust in other network participants). The low R^2 for Trust in our model (0.193) indicates substantial unexplained variance that richer trust theorizing could address.

7.7 Concluding remarks

Blockchain technology holds transformative potential for governance and sustainability in high-stakes industrial supply chains, yet realizing this potential requires a nuanced understanding of how professionals translate system perceptions into adoption decisions. This study contributes to that understanding by demonstrating that blockchain trust in the Indonesian energy sector is built not on traceability or performance promises—as much of the literature assumes—but on the foundational characteristics of system quality and usability. The Risk Awareness Paradox further complicates the conventional view that risk perception uniformly deters adoption, revealing instead that awareness and adoption can coexist and mutually reinforce in expert professional populations. Finally, the direct effect of TMS repositions organizational leadership as an independent driver of use behavior rather than a contextual amplifier of individual intention.

Taken together, these findings suggest a substantial reorientation of both theory and practice in blockchain-supply chain research. For theory, they call for stage-sensitive, context-aware, and mechanism-explicit models that move beyond generic adoption frameworks toward nuanced explanations of how trust, risk, and organizational support interact in industrial settings. For practice, they recommend that blockchain deployment strategies prioritize system reliability and user experience, leverage risk awareness as an adoption opportunity rather than a barrier, and combine voluntary adoption pathways with explicit leadership mandates. In the broader context of cleaner energy supply chains, this integrated trust-based framework offers a robust foundation for understanding and facilitating the blockchain-enabled governance transformations that critical infrastructure sectors increasingly require.

The journey toward counterfeit-free, traceable, and environmentally sustainable power plant spare parts supply chains is ultimately a journey of trust—trust in technology, trust in systems, and trust in the institutional frameworks that govern their use. This study provides an empirically grounded roadmap for that journey, placing system fundamentals, risk awareness, and organizational commitment at the center of the blockchain adoption equation.

REFERENCES

[1] Kamble, S.S., Gunasekaran, A., Sharma, R. (2020). Modeling the blockchain enabled traceability in agriculture supply chain. International Journal of Information Management, 52: 101967. https://doi.org/10.1016/j.ijinfomgt.2019.05.023

[2] Kouhizadeh, M., Saberi, S., Sarkis, J. (2021). Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers. International Journal of Production Economics, 231: 107831. https://doi.org/10.1016/j.ijpe.2020.107831

[3] Patil, R., Sawant, B., Chakote, A., Chaudhari, H., Shelke, P. (2024). Supply chain traceability for energy resources using blockchain. In 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS), Manama, Bahrain, pp. 548-552. https://doi.org/10.1109/ICETSIS61505.2024.10459652

[4] Nabil, D.H., Rahman, M.H., Chowdhury, A.H., Menezes, B.C. (2023). Managing supply chain performance using a real time Microsoft Power BI dashboard by action design research (ADR) method. Cogent Engineering, 10(2): 2257924. https://doi.org/10.1080/23311916.2023.2257924

[5] Herranz-Pascual, K., Garcia-Quincoces, E., Diez-Gaspon, I., Bachiller-Prieto, R. (2020). Moving towards for active role for smart grid users: Study about the perception of smart grids among domestic consumers in Spain (UPGRID project) (Avanzando hacia el rol activo de los usuarios de las smart grids: Estudio sobre la percepción de las redes eléctricas inteligentes entre los consumidores domésticos en España (proyecto UPGRID)). PsyEcology, 11(1): 148-160. https://doi.org/10.1080/21711976.2019.1643661

[6] Yue, Y., Fu, X. (2020). Research on medical equipment supply chain management method based on blockchain technology. In 2020 International Conference on Service Science (ICSS), Xining, China, pp. 143-148. https://doi.org/10.1109/ICSS50103.2020.00030

[7] Sahebi, I.G., Mosayebi, A., Masoomi, B., Marandi, F. (2022). Modeling the enablers for blockchain technology adoption in renewable energy supply chain. Technology in Society, 68: 101871. https://doi.org/10.1016/j.techsoc.2022.101871

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

[9] Cordeiro, M., Ferreira, J.C. (2025). Beyond traceability: Decentralised identity and digital twins for verifiable product identity in agri-food supply chains. Applied Sciences, 15(11): 6062. https://doi.org/10.3390/app15116062

[10] Venkatesh, V., Thong, J. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. Journal of the association for Information Systems, 17(5): 328-376. https://doi.org/10.17705/1jais.00428

[11] Queiroz, M.M., Fosso Wamba, S., De Bourmont, M., Telles, R. (2021). Blockchain adoption in operations and supply chain management: Empirical evidence from an emerging economy. International Journal of Production Research, 59(20): 6087-6103. https://doi.org/10.1080/00207543.2020.1803511

[12] Jung, D.H. (2022). Enhancing competitive capabilities of healthcare SCM through the blockchain: Big data

business model's viewpoint. Sustainability, 14(8): 4815. https://doi.org/10.3390/su14084815
[13] Barenji, A.V., Montreuil, B. (2022). Open logistics: Blockchain-enabled trusted hyperconnected logistics platform. Sensors, 22(13): 4699. https://doi.org/10.3390/s22134699
[14] Wang, J., Yin, S., Li, Y., Liu, C., Yang, Z. (2023). Blockchain-based regulatory framework for logistics management. In 2023 6th International Conference on Artificial Intelligence and Big Data (ICAIBD), Chengdu, China, pp. 941-945. https://doi.org/10.1109/ICAIBD57115.2023.10206236
[15] Bellet, T., Banet, A. (2023). UTAUT4-AV: An extension of the UTAUT model to study intention to use automated shuttles and the societal acceptance of different types of automated vehicles. Transportation Research Part F: Traffic Psychology and Behaviour, 99: 239-261. https://doi.org/10.1016/j.trf.2023.10.007
[16] Bere, A.B.M., Putra, R.W., Wedari, L.K. (2024). Investigation of digital rupiah acceptance using UTAUT-3 model. Indonesian Journal of Electrical Engineering and Computer Science, 35(3): 1710-1721. https://doi.org/10.11591/ijeecs.v35.i3.pp1710-1721
[17] Sihaloho, I., Nicholas, G.S., Saragi, H.S., Simamora, N.S., Turnip, Y.G. (2025). Development of electric vehicle adoption intentions in North Sumatra using UTAUT modeling. In 2025 International Conference on Computer Sciences, Engineering, and Technology Innovation (ICoCSETI), Jakarta, Indonesia, pp. 727-732. https://doi.org/10.1109/ICoCSETI63724.2025.11020305
[18] Faroqi, A., Apol Pribadi, S., Tri Lathif, M.S. (2020). Exploring online shoppers' acceptance of electronic marketplace using UTAUT and the flow theory. Journal of Physics: Conference Series, 1569(2): 022051. https://doi.org/10.1088/1742-6596/1569/2/022051
[19] Wang, X., Liu, L., Liu, J., Huang, X. (2022). Understanding the determinants of blockchain technology adoption in the construction industry. Buildings, 12(10): 1709. https://doi.org/10.3390/buildings12101709
[20] Wong, L.W., Tan, G.W.H., Lee, V.H., Ooi, K.B., Sohal, A. (2020). Unearthing the determinants of Blockchain adoption in supply chain management. International Journal of Production Research, 58(7): 2100-2123. https://doi.org/10.1080/00207543.2020.1730463
[21] Engesser, V., Rombaut, E., Vanhaverbeke, L., Lebeau, P. (2023). Autonomous delivery robots for urban last-mile logistics operations: A modified UTAUT framework. Transportation Research Procedia, 72: 1816-1823. https://doi.org/10.1016/j.trpro.2023.11.658
[22] Park, S.R., Oh, K.S. (2022). Integration of ESG information into individual investors' corporate investment decisions: Utilizing the UTAUT framework. Frontiers in Psychology, 13: 899480. https://doi.org/10.3389/fpsyg.2022.899480
[23] Hirose, S., Nakamoto, T., Taguchi, K. (2023). Chemical oxygen demand sensor based on microbial fuel cell using low-cost electrodes fabricated from waste rice husks. Resourceedings, 3(2): 25-31. https://doi.org/10.21625/resourceedings.v3i2.979
[24] Rana, S.K., Kim, H.C., Pani, S.K., Rana, S.K., Joo, M.I., Rana, A.K., Aich, S. (2021). Blockchain-based model to improve the performance of the next-generation digital supply chain. Sustainability, 13(18): 10008. https://doi.org/10.3390/su131810008
[25] Kshetri, N. (2018). 1 Blockchain's roles in meeting key supply chain management objectives. International Journal of Information Management, 39: 80-89. https://doi.org/10.1016/j.ijinfomgt.2017.12.005
[26] Chittipaka, V., Kumar, S., Sivarajah, U., Bowden, J.L.H., Baral, M.M. (2023). Blockchain technology for supply chains operating in emerging markets: An empirical examination of technology-organization-environment (TOE) framework. Annals of Operations Research, 327(1): 465-492. https://doi.org/10.1007/s10479-022-04801-5
[27] Bai, C., Sarkis, J. (2020). A supply chain transparency and sustainability technology appraisal model for blockchain technology. International Journal of Production Research, 58(7): 2142-2162. https://doi.org/10.1080/00207543.2019.1708989
[28] Zhu, Y. (2022). Research on real-time tracking algorithm of e-commerce logistics information based on blockchain technology. Computational Intelligence and Neuroscience, 2022(1): 7006506. https://doi.org/10.1155/2022/7006506
[29] Kamble, S.S., Gunasekaran, A., Gawankar, S.A. (2020). Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications. International Journal of Production Economics, 219: 179-194. https://doi.org/10.1016/j.ijpe.2019.05.022
[30] Aslam, J., Lai, K.H., Kim, Y.B., Treiblmaier, H. (2024). The implications of blockchain for logistics operations and sustainability. Journal of Innovation & Knowledge, 9(4): 100611. https://doi.org/10.1016/j.jik.2024.100611
[31] Harish, A.R., Liu, X.L., Li, M., Zhong, R.Y., Huang, G.Q. (2023). Blockchain-enabled digital assets tokenization for cyber-physical traceability in E-commerce logistics financing. Computers in Industry, 150: 103956. https://doi.org/10.1016/j.compind.2023.103956
[32] Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3): 425-478. https://doi.org/10.2307/30036540
[33] Olsen, P., Borit, M. (2018). The components of a food traceability system. Trends in Food Science & Technology, 77: 143-149. https://doi.org/10.1016/j.tifs.2018.05.004
[34] Susanty, A., Akhsan, F.A., Puspitasari, N.B. (2023). Modeling the users' acceptance and perceived usability for halal traceability system. In 2023 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, pp. 1093-1097. https://doi.org/10.1109/IEEM58616.2023.10406594
[35] Saberi, S., Kouhizadeh, M., Sarkis, J., Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. International Journal of Production Research, 57(7): 2117-2135. https://doi.org/10.1080/00207543.2018.1533261
[36] Zhang, T., Jia, F., Chen, L. (2024). Blockchain adoption in supply chains: implications for sustainability. Production Planning & Control, 36(5): 699-722. https://doi.org/10.1080/09537287.2023.2296669
[37] Roy, S., Mohapatra, S. (2022). Problems of adoption of solar power and subsequent switching behavior: An exploration in India. International Journal of Energy

Sector Management, 16(1): 78-94. https://doi.org/10.1108/IJESM-08-2020-0015
[38] Singh, N., Jung, I., Han, H., Ariza-Montes, A., Vega-Muñoz, A. (2022). Green information system (GIS) model in the conference sector: exploring attendees' adoption behaviors for conference apps. Psychology Research and Behavior Management, 15: 2229-2243. https://doi.org/10.2147/PRBM.S370657
[39] Zhai, H., Yang, X., Xue, J., Lavender, C., et al. (2021). Radiation oncologists' perceptions of adopting an artificial intelligence–assisted contouring technology: Model development and questionnaire study. Journal of Medical Internet Research, 23(9): e27122. https://doi.org/10.2196/27122
[40] Fedorko, I., Bačik, R., Gavurova, B. (2021). Effort expectancy and social influence factors as main determinants of performance expectancy using electronic banking. Banks and Bank Systems, 16(2): 27-37. https://doi.org/10.21511/bbs.16(2).2021.03
[41] Ghode, D., Yadav, V., Jain, R., Soni, G. (2021). Blockchain adoption in the supply chain: an appraisal on challenges. Journal of Manufacturing Technology Management, 32(1): 42-62. https://doi.org/10.1108/JMTM-11-2019-0395
[42] Barratt, M. (2016). Autobiography, time, and documentation in the performances and auto-archives of Carolee Schneemann. Visual Resources, 32(3-4): 282-305. https://doi.org/10.1080/01973762.2016.1229386
[43] Delgado, F., Garrido, S., Bezerra, B.S. (2025). Barriers to visibility in supply chains: Challenges and opportunities of artificial intelligence driven by industry 4.0 technologies. Sustainability, 17(7): 2998. https://doi.org/10.3390/su17072998
[44] de Jesus, A., Lammi, M., Domenech, T., Vanhuyse, F., Mendonça, S. (2021). Eco-innovation diversity in a circular economy: Towards circular innovation studies. Sustainability, 13(19): 10974. https://doi.org/10.3390/su131910974
[45] Rinaldi, M., Caterino, M., Fera, M., Abbate, R., Daniele, U., Macchiaroli, R. (2025). Circular economy strategy selection through a digital twin approach. Applied Sciences, 15(13): 7016. https://doi.org/10.3390/app15137016
[46] Durnagöz, S., Huber, M.F., Mayer, M., Reimann, P. (2024). An approach to inline monitoring of the electrode state in resistance spot welding. International Journal of Electrical and Electronic Engineering & Telecommunications, 13: 245-251. https://doi.org/10.18178/ijeetc.13.3.245-251
[47] Nawaz, A., Afzal, A., Khatibi, A., Shankar, A., et al. (2025). Role of artificial intelligence in halal authentication and traceability: A concurrent review. Food Control, 169: 111003. https://doi.org/10.1016/j.foodcont.2024.111003
[48] Hastig, G.M., Sodhi, M.S. (2020). Blockchain for supply chain traceability: Business requirements and critical success factors. Production and Operations Management, 29(4): 935-954. https://doi.org/10.1111/poms.13147
[49] Radhakrishnan, J., Chattopadhyay, M. (2020). Determinants and barriers of artificial intelligence adoption–a literature review. In International Working Conference on Transfer and Diffusion of IT, India, pp. 89-99. https://doi.org/10.1007/978-3-030-64849-7_9
[50] Sharma, S., Singh, G., Pratt, S. (2025). Applying a technology acceptance model to understand digital-free tourism. Tourism Recreation Research, 50(2): 229-246. https://doi.org/10.1080/02508281.2023.2252680
[51] Ringle, C.M., Wende, S., Becker, J.M. (2022). SmartPLS 4. http://www.smartpls.com.
[52] Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M. (2021). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage Publications. https://uk.sagepub.com/en-gb/eur/a-primer-on-partial-least-squares-structural-equation-modeling-pls-sem/book270548.
[53] Zhao, X., Lynch Jr, J.G., Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2): 197-206. https://doi.org/10.1086/651257
[54] Nitzl, C., Roldan, J.L., Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. Industrial Management & Data Systems, 116(9): 1849-1864. https://doi.org/10.1108/IMDS-07-2015-0302
[55] DeLone, W.H., McLean, E.R. (2003). The DeLone and McLean model of information systems success: A ten-year update. Journal of Management Information Systems, 19(4): 9-30. https://doi.org/10.1080/07421222.2003.11045748
[56] Ewert, R., Grahle, A., Martins-Turner, K., Syré, A.M., Nagel, K., Göhlich, D. (2021). Electrification of urban waste collection: Introducing a simulation-based methodology for technical feasibility, impact and cost analysis. World Electric Vehicle Journal, 12(3): 122. https://doi.org/10.3390/wevj12030122
[57] El Midaoui, M., Laoula, E.B., Qbadou, M., Mansouri, K. (2021). Logistics tracking system based on decentralized IoT and blockchain platform. Indonesian Journal of Electrical Engineering and Computer Science, 23(1): 421-430. https://doi.org/10.11591/ijeecs.v23.i1.pp421-430
[58] Chang, C.K. (2020). Blockchain for integrated nuclear power plants management system. Information, 11(6): 282. https://doi.org/10.3390/info11060282
[59] Goncalves, J.N., Cortez, P., Carvalho, M.S. (2021). K-means clustering combined with principal component analysis for material profiling in automotive supply chains. European Journal of Industrial Engineering, 15(2): 273-294. https://doi.org/10.1504/EJIE.2021.114009
[60] Martins-Turner, K., Grahle, A., Nagel, K., Göhlich, D. (2020). Electrification of urban freight transport-a case study of the food retailing industry. Procedia Computer Science, 170: 757-763. https://doi.org/10.1016/j.procs.2020.03.159
[61] Sharma, A., Sharma, A., Singh, R.K., Bhatia, T. (2023). Blockchain adoption in agri-food supply chain management: An empirical study of the main drivers using extended UTAUT. Business Process Management Journal, 29(3): 737-756. https://doi.org/10.1108/BPMJ-10-2022-0543