Digital Synergy: Examining How IoT, Blockchain and AI Collectively Improve Supply Chain Transparency

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ABSTRACT

This research is aimed at investigating the role of new technologies in supply chain transparency and traceability. In particular, the study focuses on the ways the emergent technologies, such as the internet of things (IoT), blockchain (BC), and artificial intelligence (AI) transform the visibility and accountability within the network of supply chains. Data were collected by a survey-based approach where the respondents were professionals working in different fields of the supply chain and the data were analyzed using structural equation modelling to determine the technological pathways that play a significant role in enhancing transparency, traceability, and accountability. The results indicate that IoT can be used to take data in real-time and monitor it continuously, BC can be used to ensure that data are stored in a secure and tamper-proof manner, and AI can be used to enhance predictive analytics and automated decision-making. All these technologies provide better data integrity, access, and accuracy and minimize the risk of manual tracking and disjointed information systems. They also help to detect disruption faster and enhance coordination between stakeholders, which contributes to the higher adherence of regulatory and quality standards. In general, the paper has shown that the combined application of the IoT, BC, and AI can bring certain benefits to the supply chain in terms of transparency and resilience significantly, which supports their role in contemporary supply chain remodeling.

Keywords: Internet of Things, Blockchain, Artificial Intelligence, Supply Chain Transparency
JEL Classifications: L23; M11; O33

1. INTRODUCTION

The modern global market is an integrated environment where the supply chains are miles apart, incorporating producers and consumers subjected to varying law provisions. Although this complexity encourages development of international trade, it equally creates a lot of challenges especially in relation to transparency and traceability. The visibility in the supply chain has been seen not only as a convenience, but it has also become an essential requirement in the process of making. This compulsion is particularly acute within the agri-food sector, where clients demand quality, safety, and ethically sourced goods and services (Hasan and Habib, 2023).

The solution of these complex problems and the reaction to the constantly increasing demand of supply chain visibility require the strategic and simultaneous introduction of sophisticated technologies. This study investigates the interdependence of the internet of things (IoT), blockchain, and artificial intelligence (AI) to improve the visibility of the supply chain, especially

in the context of the agri-food supply chain. The ideal model of transparency is sequential and combined: at the first stage, the IoT creates the data layer, then, blockchain provides the security of data integrity and authenticity, and finally, AI creates high-order analysis possibilities and insights into operations (Afarat et al., 2024; Mukhtar et al., 2020). This closed system will bring competitive advantages through better performance and responsiveness, thus creating an environment of transparent, trustful, and operationally efficient supply chain (Amiri et al., 2025). It is argued that the overall impact of such technologies can be multiplicative, that is, it can be even more effective than any single technology and therefore contributes to more effective supply-chain decision-making (Amiri et al., 2025).

The internet of things (IoT), blockchain (BC), and artificial intelligence (AI) are becoming more important in transforming supply-chain operations by enhancing the visibility and data integrity, as well as the ability to make decisions, in real time (Ahmed et al., 2022; Yekeen et al., 2024). IoT allows constant data recording in supply-chain operations, and the information is protected and impossible to modify as the result of blockchain. Using these credible sources of data, AI forms predictive insights and assists in proactive reactions to operational dilemma. A combination of these technologies has formed an integrated and transparent digital ecosystem that leads to improved traceability, minimized risks, and enables quick and evidence-based supply-chain decisions.

This work has a task to explore the applications and relationships between internet of things (IoT), blockchain (BC), and artificial intelligence (AI) in developing supply chain transparency (SCT) as part of the suggested theoretical framework.

This research aims:
- To empirically validate an integrated technological pathway in which IoT adoption and blockchain capability enables AI utilisation, and AI subsequently enhances supply-chain transparency, thereby establishing how these interdependent technologies collectively strengthen visibility, traceability, and information integrity across modern supply chains.

The study makes valuable contributions by attaining these goals. In the conceptual sense, it enhances the research on how important digital technologies engage with one another to aid supply chain transparency. Applied-wise, it gives industry practitioners and policy makers a path forward towards integrating and optimizing these technologies to create transparent, resilient and reliable supply chains, especially in the agri-food sector.

2. CONCEPTUAL FRAMEWORK AND HYPOTHESES

The suggested study is based on the premise that the internet of things (IoT) and blockchain (BC) offer the foundational data and security needed to have artificial intelligence (AI) operational in supply chains. IoT can provide real-time sensor data and BC can guarantee that the information is secure, cannot be tampered with

and can be verified. The integration of these technologies allows AI to provide enhanced analytical solutions that facilitate decision-making in operations and supply chains visibility by means of better information sharing and collaborative networks (Kashem et al., 2023; Peesapati, 2024; Hasan et al., 2023).

H_1: IoT implementation positively impacts blockchain implementation in supply chains.

Blockchain adoption benefits from IoT's real-time data collection and monitoring capabilities, which create a favourable environment for its implementation. IoT helps blockchain to provide transparent, irrevocable, reliable records of tracking and verifying goods by creating large volumes of operational data (Nasrun et al., 2025).

H_2: The use of blockchain positively impacts AI usage in supply chains.

The blockchain ensures that data is intact, authentic and transparent, which is necessary to allow AI algorithms to conduct correct analytics, predictions and decisions. The AI-enabled improvements in logistics, demand prediction, and inventory management are reinforced by the safe and reliable data that is generated using blockchain (Nasrun et al., 2025).

H_3: The implementation of AI positively influences the transparency of the supply chain.

With high-quality data provided by IoT and blockchain, AI systems could be used to perform advanced analytics, detect anomalies, make predictive insights and view real-time monitoring across the entire chain of supply. Such features increase transparency, support the detection of bottlenecks, enhance compliance, and avail stakeholder information (which is actionable), thus enhancing the visibility of the supply chain (Arabzadeh et al., 2024; Asbeetah et al., 2025; Li et al., 2024).

The empirical model is based on these hypotheses, which allow testing the sequential pathway IoT → Blockchain → AI → transparency with the help of the obtained data.

3. REVIEW OF LITERATURE

The current section critically analyses the available literature that forms the basis of these technological constructs and evaluates their overall impact on the transparency of supply chains.

3.1. Internet of Things (IoT)

IoT is widely recognized in the literature as a central variable due to its role in enabling real-time data collection across supply chains. Udeh et al. (2024) refer to IoT devices (RFID, GPS trackers, environmental sensors, etc.) as the key to permanent visibility of product movement and condition, whereas Ahmed et al. (2021) highlight its functions as the factor in enhancing responsiveness in operations, including optimization of routes and accuracy of tracking. According to Hasan et al. (2024), the IoT holds significance in very sensitive areas like agri-food,

where the temperature, safety, and quality of food should be measured constantly. Collectively, prior studies establish IoT as the foundational data-generation layer in supply chains.

3.2. Blockchain

According to Thakur (2023), blockchain is defined as a cryptographically secure register that inhibits the manipulation of data Tokkozhina et al., (2022), whereas Fu et al. (2023) demonstrate that blockchain reduces the agency issues and increases trust by decreasing the information asymmetry. Dasaklis et al. (2022) show the essence of blockchain in traceability systems, particularly in such safety-related settings, and Wamba and Queiroz (2020) highlight the capability of blockchain to provide permanent and transparent records of products. In line with this, Qian and Papadonikolaki (2020) and Wang et al. (2020); Tokkozhina et al., (2022) state that blockchain enhances operational transparency by generating verifiable records that can be accessed by the stakeholders (Khairunnisa et al., 2024). Noteworthy, Gomez-Marain et al. (2023) show that blockchain serves to validate the data of the IoT sensors, which means that only authenticated and non-tampered information can enter the system. Collectively, these works position blockchain as the data-integrity and trust-building layer.

3.3. Artificial Intelligence (AI)

AI is widely recognized in the literature as the decision-optimization and analytics tier of digital supply chains. Daios et al. (2025) single out AI as a disruptive tool that can optimize demand forecasting, support pattern recognition, and improve logistics, and Mohsen (2023) can prove the usefulness of AI in optimizing operational visibility and the ability to identify risks. Maniatis (2025) goes on to state that AI assists in predictive and real-time decision-making, combining and analyzing extensive amounts of supply chain data. Furthermore, as explained by Kashem et al. (2023), AI uses secure and tamper-free data, which is often delivered by blockchain, to conduct reliable analysis, and Peesapati (2024) points to the capability of AI to integrate multi-source data to generate actionable insights, which make it more visible. Accordingly, AI is theorized to have a direct positive effect on supply chain transparency.

3.4. Supply Chain Transparency (SCT)

Transparency is critical because regulatory requirements are rising, ethical sourcing factors, and consumer demands, whereas Ahmed and MacCarthy (2023) consider it crucial to guarantee compliance, quality assurance, and visibility within distributed systems. Hasan et al. (2023) emphasize the applicability of transparency in agri-food systems, in which traceability and quality evidence have become essential. As (Iftikhar et al., (2024); Afarat et al., 2024); Massaro et al., (2023); Pal, (2023) show, combining IoT, blockchain, and AI leads to the much-improved visibility, accountability, and responsiveness throughout the supply chain. SCT represents the final outcome in the theoretical model, capturing the improvement in visibility, traceability, and information clarity.

3.5. Research Gaps and the Current Study

Although the IoT, blockchain and artificial intelligence are gaining more acceptance in the industry sector, the existing literature focuses more on highlighting the individual benefits of any of the technologies, as opposed to the combination of their respective impacts on supply-chain transparency. As a result, there is limited understanding of how these technologies interoperate and the extent to which their interdependencies influence visibility, traceability, and information integrity. The main gap in the literature is that none of the existing studies provide an integrated framework examining IoT, blockchain, AI, and transparency simultaneously. To fill this gap, the current research paper proposes and empirically tests a conceptual framework that brings together these technologies, specifically through the lens of how they are interrelated to one another in the agri-food supply chain.

4. METHODOLOGY

The research design was a cross-sectional, quantitative study, which was used to examine the complex relationships between the internet of things (IoT), blockchain, artificial intelligence (AI), and supply-chain transparency (Jain et al., 2021). 5A structured electronic questionnaire was used to collect data on 413 supply-chain professionals who were recruited across the various industries, with some being manufacturing, logistics, and retail. The stratified random sampling process ensured a representative cohort especially among the personnel involved in the operations, quality and information technology functions. Despite the sample being more representative of the members of the technology-intensive sectors-most evidently, in the agri-food industry, where the implementation of the digital technologies follows the strong trend; however, the overall sample size was considered sufficient for robust statistical analysis.

The four major constructs, which include IoT adoption, blockchain adoption, AI deployment, and perceived supply-chain transparency, were operationalised through multi-item scales, which were based on existing literature. Five items internet of things (IoT1-IoT5), blockchain (BC1-BC5), artificial intelligence (AI1-AI5), and Supply chain transparency (SCT1-SCT5) were used to measure each of the constructs. The respondents were asked to rate each of the items on the five-point Likert scale that ranging from strongly disagree (1) to strongly agree (5). Construct validity was determined by means of the confirmatory factor analysis (CFA), whereas reliability was assessed by Cronbach's α and McDonalds ω.

Jamovi was used to perform structural equation modelling to test the hypotheses. Since the survey data is ordinal, the diagonally weighted least squares (DWLS) estimator using robust standard errors was used. The traditional indices were used to evaluate the model fit, including comparative fit index (CFI), tucker-lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The hypothesised relationships were evaluated using standardised path coefficients and their significance levels.

5. RESULTS AND DISCUSSION

The results provided in the analysis are reliability assessment, EFA, CFA and SEM that were all performed in Jamovi to ensure consistency of the measurement model and the structural model evaluation.

5.1. Reliability Analysis

The measurement scales of each construct were assessed using the reliability coefficients of Cronbach's α and McDonald's ω. how consistently the items measure their respective constructs (Table 1).

The overall scale reliability statistics for the combined set of items suggested excellent internal consistency (Mean = 2.97, SD = 0.462, Cronbach's α = 0.914, McDonald's ω = 0.915).

Values of Cronbach's α and McDonald's ω were both above the accepted value of 0.70 and in fact were soundly above 0.90 which illustrates excellent reliability (Mwangi et al., 2025, Nartova-Bochaver et al., 2021). Also, McDonald's ω is preferred for confirming reliability and strong internal consistency to the scales.

5.2. Exploratory Factor Analysis

An exploratory factor analysis (EFA) was followed by the confirmatory factor analysis (CFA), which was aimed at revealing the underlying structure of 20 measurement items reflecting four constructs, namely IoT, BC, AI, and SCT (Table 2). The EFA established a four-factor solution that was coherent with the theoretical model and the item loadings were high and uniqueness values low, which points to high initial dimensionality and discriminant validity (Basit et al., 2024). A rotation (oblimin) was done in order to enable correlations between factors, which is suitable on technology-related constructs that are theoretically related. The EFA showed excellent model fit an RMSEA of 0.0135, TLI of 0.996, and the Chi-square test was non-significant (P = 0.268), indicating a good model fit. The findings were also an additional confirmation of the measurement scales and offered a solid basis to carry on with the confirmatory factor analysis.

5.3. Confirmatory Factor Analysis

After the EFA was finished, it was time to perform the confirmatory factor analysis (CFA). This analysis will help evaluate the psychometric properties of the measurement model in more detail, such as its convergent and discriminatory validity, as well as general model fit of the measurement model. There were four variables in the model of the CFA, and for every one of them, there were five measurement items that were used.

5.3.1. Measurement model assessment

As Figure 1 illustrates, the study assumes the relationships between blockchain integration, AI abilities, and supply chain transparency The standardized factor loadings from the CFA, displayed in Table 3, show how strongly connected each observed item is to each of the latent constructs. Since all factor loadings are statistically significant (P < 0.001), this is further proof for the convergent validity of the scales. More than half of the standardized factor loadings were above the 0.70 threshold (Al-

Swidi et al., 2024), ranging from 0.698 (SCT4) to 0.813 (AI2). With a value of 0.698, the item SCT4 is below 0.70 and while this is technically the weakest factor loading, it is still a statistically significant factor loading and is acceptable in terms of overall model fit.

Table 1. Reliability analysis

Scale reliability statistics				
Costruct	Mean	SD	Cronbach's α	McDonald's ω
Scale	2.97	0.462	0.914	0.915

Table 2: Model fit measures

Model	RMSEA 90% CI		Model test					
RMSEA	Lower	Upper	TLI	BIC	χ^2	Degrees of freedom	P-value
0.0135	0.00	0.0290	0.996	−574	125	116	0.268

Table 3: Standardized factor loadings for the measurement model

Factor	Indicator	Stand. Estimate	P-value
IOT	IOT1	0.734	<0.001
IOT	IOT2	0.789	<0.001
IOT	IOT3	0.753	<0.001
IOT	IOT4	0.777	<0.001
IOT	IOT5	0.787	<0.001
Blockchain	BC1	0.745	<0.001
Blockchain	BC2	0.72	<0.001
Blockchain	BC3	0.794	<0.001
Blockchain	BC4	0.779	<0.001
Blockchain	BC5	0.78	<0.001
AI	AI1	0.754	<0.001
AI	AI2	0.813	<0.001
AI	AI3	0.786	<0.001
AI	AI4	0.755	<0.001
AI	AI5	0.774	<0.001
SC Transparency	SCT1	0.758	<0.001
SC Transparency	SCT2	0.768	<0.001
SC Transparency	SCT3	0.745	<0.001
SC Transparency	SCT4	0.71	<0.001
SC Transparency	SCT5	0.77	<0.001

Table 4: Inter-factor correlations from CFA

Factors	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1			
Factor 2	0.418	1		
Factor 3	0.389	0.497	1	
Factor 4	0.474	0.451	0.515	1

Table 5: Goodness-of-fit statistics for the CFA model

Fit index	Value	Threshold for good fit
Chi-square	182	P>0.05
Degrees of freedom	164	
P	0.154	
CFI	0.996	P>0.95
TLI	0.995	P>0.95
SRMR	0.0275	P<0.08
RMSEA	0.0165	P<0.05
RMSEA 90% CI	0.00-0.0287	

5.3.2. Discriminant validity
All of the inter-factor correlations (covariances) exhibited positivity and significance, ranging from 0.389 to 0.515 (Table 4). This shows that the constructs of interest are connected, but distinct from one another, thereby substantiating the discriminant validity.

5.3.3. Measurement model fit
The CFA model was assessed in terms of its adaptability of the model with a range of traditionally established fit indices, as shown in Table 5. The Chi-square test ($\chi^2 = 182$, 164 df, P = 0.154) was not statistically significant, which means that the modelled variance-covariance matrix is not an inadequate fit to the observed data and, thus, it is a satisfactory model fit (Rehman and Jalees, 2025). Other indices also indicated the acceptability of the model (Alonge et al., 2021): The comparative fit index (CFI = 0.996) was much greater than the recommended value of 0.95, the tucker-lewis index (TLI = 0.995) was also much greater than the 0.95 mark, the Standardized root mean square residual (SRMR = 0.0275) was significantly less than the 0.08 level, and the RMSEA value of 0.0165, with a 90% CI of 0.00-0.0287, further confirmed close model fit. The model has also been used to describe the association between the measured indicators and other constructs.

5.4. Structural Equation Modelling
After the measurement model was validated, for the hypotheses H_1, H_2, and H_3, structural equation modelling was conducted to test the relationships within the latent variables. Due to the ordinal scale measurement in the variables, the diagonally weighted least squares (DWLS) method for estimation was used, in addition to robust standard errors to take into consideration possible non-normality within the data. After 33 iterations, the model converged successfully.

The standardized path coefficients and structure model are shown in Figure 2 which were obtained after the analysis. Structural equation model is the relationship of the IoT adoption, blockchain capability, AI capability, and supply chain transparency in a supply chain that uses technology. Measurement properties of all constructs were high with factor loadings of most being above 0.70 which is a good indicator of strong reliability and convergent validity. The model shows that IoT adoption has a positive impact on Blockchain capability ($\beta = 0.650$, P < 0.001), that is, sensor-generated real-time data generates a necessity to have secure and verifiable digital records. Blockchain capability, in its turn, affects AI capability in a positive manner that is significantly strong ($\beta = 0.688$, P < 0.001), which means that trusted tamper-proof data spaces lead to the performance and implementation of AI-based analytics. Finally, the AI capability impacts supply chain transparency the most ($\beta = 0.695$, P < 0.001), i.e. AI-based monitoring, predicting, and information detection affect positively, albeit significantly, the enhancement of the visibility, traceability, and clarity of the information across the supply chain. Overall, this model can be regarded as a technological and technological effect whereby the foundational layer is the IoT and the blockchain, the middle layer is the AI and the final product of this interconnected digital system is the supply chain transparency.

5.4.1. Structural model fit
Table 6 shows both classical and robust fit indices used to estimate the overall the fitness of the structural model. The Chi-square statistic of the user model was significant ($\chi^2 = 690$, df = 167, P = 0.001); more precisely, this outcome is expected, because 2 is very sensitive to sample size and, therefore, would indicate significant results in large samples even with a well-fitting model, Shi et al., 2022). As a result, further strong indices were tested to measure the sufficiency of the model. The model demonstrated acceptable to strong fit on the following indicators: Robust SRMR was 0.076, therefore, meeting the recommended threshold of 0.08; robust RMSEA was 0.068 with a 95% confidence interval of 0.056-0.080 and a P = 0.009 and so it does not exceed the standard cutoff of 0.08 defining adequate fit; robust CFI and TLI values were 0.939 and 0.931 respectively and these exceed the traditional combined, these strong fit indices testify to the fact that the structural model provides a good and reliable representation of the proposed relationships in the current study (Ali et al., 2024).

5.4.2. Hypothesis testing
The results of the structural model analysis are shown in Table 7. All proposed paths were statistically significant, and are in the direction predicted, thus confirming H_1, H_2 and H_3.
- H_1: The internet of things has a positive impact on the adoption and implementation of blockchain in supply chains. The path from IOT → BC was positive and significant ($\beta = 0.650$, P < 0.001). Hence, H_1 was supported. It shows that a standard deviation increase in IoT results in a blockchain capability increase of 0.650 standard deviation.
- H_2: Blockchain positively impacts the adoption and integration of artificial intelligence in supply chains. The path from BC → AI was positive and significant ($\beta = 0.688$, P < 0.001).

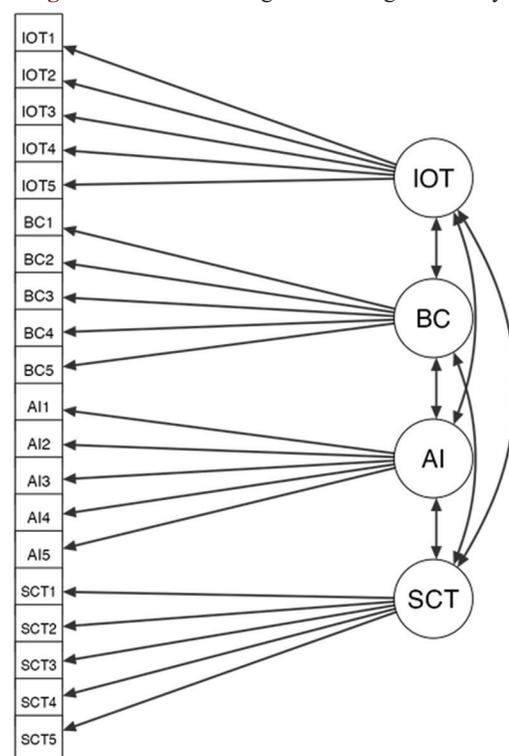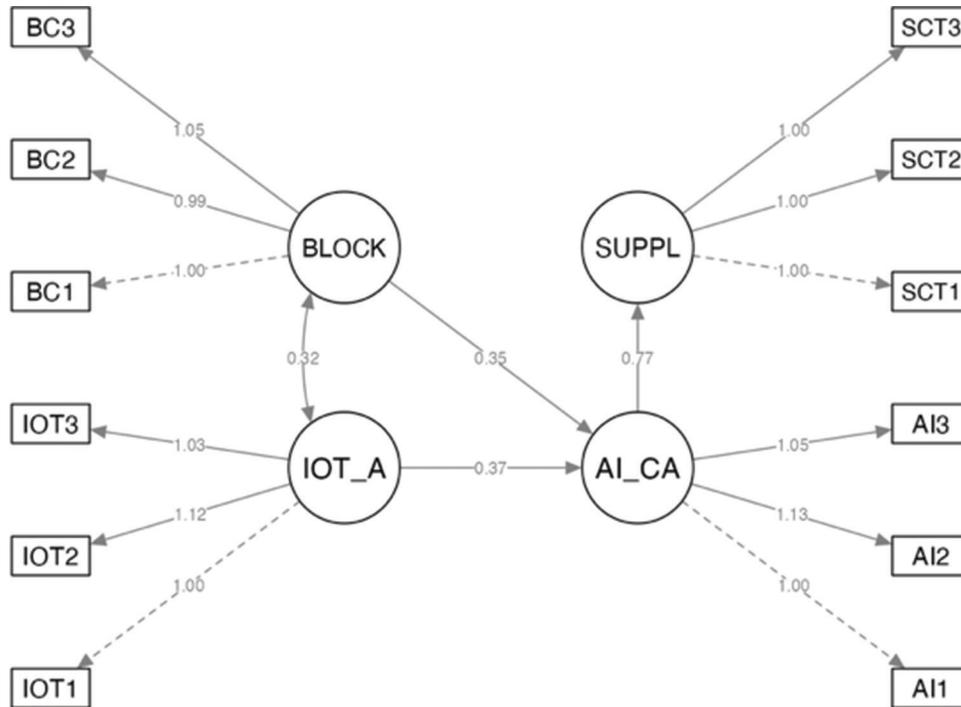**Figure 1:** Factors loading and convergent validity

Figure 2: Structural equation modelling path diagram (using Jamovi)

IOT_A: IoT adoptability, Block: Blockchain, AI_CA: AI capability, Suppl: Supply chain transparency

Table 6: Goodness-of-fit statistics for the structural model

Type	χ^2	Degrees of freedom	P-value	SRMR	RMSEA	RMSEA lower	RMSEA upper	RMSEA P	CFI	TLI
Classical	690	167	<0.001	0.089	0.087	0.081	0.094	<0.001	0.978	0.975
Robust				0.076	0.068	0.056	0.08	0.009	0.939	0.931

Table 7: Standardized path coefficients for the structural model

Dependent variable	Independent variable	Standardized estimate (β)	P-value	Hypothesis supported
BC	IOT	0.65	<0.001	Yes (H₁)
AI	BC	0.688	<0.001	Yes (H₂)
SCT	AI	0.695	<0.001	Yes (H₃)

Hence, H_2 was supported. It implies that a one standard deviation increase in BC capability results in an increase of AI capability by 0.688 standard deviation.

- H_3: Artificial Intelligence positively influences supply chain transparency. The path from AI → SCT also supports H_3 positively and significantly (β = 0.695, P < 0.001) indicating that a one standard deviation increase in AI capability results in a 0.695 standard deviation increase in supply chain transparency (Liu et al., 2025).

5.5. Key Findings

The reliability test demonstrated a high internal consistency as the Cronbach α (0.914) and McDonald ω (0.915) values were both above the recommended level (0.70) (Mwangi et al., 2025; Nartova-Bochaver et al., 2021). The exploratory factor analysis supported a four-factor model that was consistent with the theoretical grouping of IoT, blockchain, AI, and supply chain transparency, and which had strong indicators of model-fit (RMSEA = 0.0135, TLI = 0.996, χ^2 P = 0.268).

Further confirmation of the measurement model was done by confirmatory factor analysis which showed a high degree of fit (CFI = 0.996, TLI = 0.995, SRMR = 0.0275, RMSEA = 0.0165). There was also an acceptable-to-good overall fit (Robust SRMR = 0.076; Robust RMSEA = 0.068; Robust CFI = 0.939; Robust TLI = 0.931) obtained with structural equation modelling. All three structural paths were positive and statistically significant (P < 0.001), IoT has a positive impact on the adoption of BC (β = 0.650). The adoption of BC has a positive impact on the adoption of AI (β = 0.688). AI has a significant positive impact on SCT (β = 0.695).

6. DISCUSSION

This paper shows that the internet of things (IoT), blockchain (BC), and artificial intelligence (AI) can be used as complementary technologies that work together to increase the transparency of supply chains. The strong positive correlations between the constructs indicate that supply chain visibility is more and more becoming a factor of integrated digital architectures and less of single-technology-based solutions.

H_1 is supported by the previous studies (Udeh et al., 2024; Gonzalez-Amarillo et al., 2021), the IoT devices offer real-time and continuous information on product movements and conditions. As the results show, such a stable stream of operational data supports the adoption of blockchains because it presents an unchangeable

format in which events generated by IoT can be logged (Gómez-Marín et al., 2023). This affirms that IoT has become a pillar on which secure digital traceability is anchored.

The confirmation of H_2 supports the theoretical view that the value of blockchain goes beyond transparency to enable advanced analytics. Blockchain guarantees integrity, authenticity and anti-tampering of data which is critical in effective AI modelling. This is in line with previous research, which demonstrated that AI performance is better in offering accurate predictions and finding anomalies in case it is trained with reliable information (Kashem et al., 2023; Mohsen, 2023). Thus, blockchain not only ensures the integrity of information flows but also enables the implementation of AI by establishing a stable data space.

The strong support for H_3 further places AI as the intelligence layer in transforming the secure and validated data to actionable insights. AI also improves visibility and detects risks, inefficiencies, and predicts disruptions, which are highlighted in the earlier literature (Daios et al., 2025; Maniatis, 2025).

In general, this paper offers empirical data on a digital route that sequentially includes IoT → BC → AI → SCT to show that transparency is the resultant effect of data creation, data protection, and smart analytics. These findings highlight the strategic importance of integrating IoT, blockchain, and AI to strengthen trust, compliance, and data-driven decision-making in modern supply chains. These results further reinforce the importance of coordinated digital integration and emphasize that the organizations need to integrate these technologies in a way that can enable them to obtain the full benefits of transparent and reliable supply chain operations.

7. CONCLUSION

This research aimed to investigate the impact of the internet of things, blockchain technology, and artificial intelligence as a combination to provide supply chain transparency. With the help of the answers to 413 supply chain professionals, the finding proved that the proposed measurement and structural models were reliable and theoretically correct. Each of the three hypotheses was successful and showed that there is a strong sequential direction, according to which the IoT allows the adoption of Blockchain, the latter allows using AI, and the latter makes the whole system much more transparent. These results affirm the aims and objectives of the research since they demonstrate the dynamics of the three digital technologies and how they lead to visibility, traceability, and reliable information flows in contemporary supply chains. The study contributes to the theoretical knowledge because it empirically proves the interdependent model of technology-integration instead of considering these innovations as independent instruments. In practice, the study points out that organisations have to implement IoT, blockchain, and AI in a coherent way to experience significant outcomes of transparency. The study provides an organised guidance to companies that need to ensure robustness, boost the decision-making processes, and create more trusted and robust supply chain systems by defining how these technologies augment each other.

7.1. Theoretical Implications

The current state of research contributes a lot to the theoretical knowledge on technology integration in supply chain management. To begin with it empirically supports the sequential and interrelated model according to which the adoption and effectiveness of one technology precondition the next, which results in better Supply Chain Transparency. The application of the structural model has a potent contribution to the researcher who intends to comprehend the implementation of various technologies in multifaceted systems.

7.2. Practical Implications

The findings provide easy-to-follow practical managerial action plans. Companies that want to gain a higher level of multi-dimensional supply chain transparency need to focus their concurrent investments on the triad of IoT, Blockchain, and AI. High-provenance, quality, and ethically sourced products like those in the agri-food sector are industries that benefit a lot in increasing consumer satisfaction and regulation addressing this integrated tech stack. Moreover, companies that want to optimize and manage these complexes of technologies will have to invest in talent development, create successful data governance structures, and apply effective technologies.

7.3. Limitations and Future Research

Although this study has strong findings, there are a number of limitations associated with the study. Longitudinal designs should be taken into consideration in future studies to be able to show causal relationships through time. Secondly, the common methods bias is a possibility due to the use of self-report surveys. This could be minimized by future researches by gathering more objective data or utilizing various methods of data collection. The proposed research question of potential mediators or moderators may be further developed into understanding how these technologies play a role in making supply chains visible.

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