

Drivers of AI Adoption in Smart Supply Chains: An Empirical Study of Readiness, Trust, and the Insignificance of Perceived Risk.

Nor Ratna Masrom^{1*}, Wan Hasrulnizam Wan Mahmood², Al Amin Mohamed Sultan²

¹Fakulti Pengurusan Teknologi dan Teknousahawanan, Universiti Teknikal Malaysia Melaka

²Fakulti Teknologi dan Kejuruteraan Industri dan Pembuatan, Universiti Teknikal Malaysia Melaka

DOI: <https://dx.doi.org/10.47772/IJRISS.2026.10200346>

Received: 25 February 2026; Accepted: 02 March 2026; Published: 10 March 2026

ABSTRACT

Artificial Intelligence (AI)-enabled Smart Supply Chain Management (SSCM) systems are increasingly implemented within manufacturing organizations to enhance operational efficiency and strategic decision-making. While perceived risk is widely recognized as a deterrent in technology adoption research, its explanatory role in institutionalized business-to-business (B2B) environments remains under-theorized. This study investigates the determinants of AI-enabled SSCM system usage among Malaysian manufacturing firms, focusing on Effort Expectancy, Technology Readiness, Trust, and Perceived Risk. Using survey data from 308 manufacturing professionals, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test the proposed relationships. To complement explanatory modelling, machine learning techniques including Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) were applied to assess predictive capability. The results indicate that Effort Expectancy, Technology Readiness, and Trust significantly influence SSCM usage behaviour, whereas Perceived Risk does not exhibit a significant effect. Drawing on institutional theory and organizational risk absorption perspectives, the findings suggest that governance mechanisms and formal safeguards attenuate the behavioural impact of perceived uncertainty in B2B contexts. This study contributes theoretically by identifying an institutional boundary condition of perceived risk in AI adoption and methodologically by integrating SEM with validated predictive AI modelling.

INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) technologies has significantly transformed supply chain operations by enabling real-time data analytics, predictive decision-making, and enhanced operational efficiency. In recent years, Smart Supply Chain Management (SSCM) systems have emerged as an important technological innovation that integrates intelligent analytics platforms with human decision-making processes to improve supply chain visibility, responsiveness, and coordination within manufacturing organizations. Despite the potential benefits of SSCM implementation, the adoption of intelligent supply chain systems remains influenced by behavioural and organizational factors, particularly in high-stakes business-to-business (B2B) environments where operational decisions are complex and resource-intensive.

Perceived risk has traditionally been identified as a critical determinant of technology adoption in both consumer and organizational information systems research. Technology adoption models such as the Unified Theory of Acceptance and Use of Technology (UTAUT2) suggest that risk-related perceptions may influence users' willingness to accept and utilize new technological systems. However, while perceived risk has been extensively examined in consumer-oriented technology adoption contexts, its role in the adoption of AI-enabled systems within B2B manufacturing environments remains comparatively under-theorized. In organizational supply chain settings, technology adoption decisions are often collective in nature and supported by formal institutional mechanisms such as governance policies, vendor agreements, and implementation safeguards, which may reduce the influence of individual perceptions of technological risk.

Although prior studies have incorporated perceived risk into extended UTAUT and digital adoption frameworks, limited research has examined whether risk perceptions retain explanatory power in institutionalized B2B

manufacturing environments characterized by formal governance structures and collective decision-making processes. This study addresses this gap by theoretically reinterpreting the role of perceived risk through institutional and organizational risk absorption lenses, thereby extending adoption theory beyond individual cognition toward structurally embedded organizational contexts.

This study aims to examine the determinants influencing SSCM system usage behaviour among Malaysian manufacturing firms. Using survey data obtained from 308 manufacturing organizations, this study investigates whether perceived risk significantly influences SSCM adoption alongside other behavioural determinants, including Effort Expectancy, Technology Readiness, and Trust.

Theoretical Background and Hypotheses

Smart Supply Chain Management Adoption in Manufacturing Organizations

Smart Supply Chain Management (SSCM) systems represent a technological advancement that integrates digital platforms, analytics tools, and decision-support mechanisms to enhance operational efficiency within manufacturing supply chains. In organizational environments, SSCM adoption involves the interaction between technological capabilities and human decision-making processes. Therefore, the successful implementation of SSCM systems is not determined solely by technical performance but also by users' perceptions of system usability, organizational preparedness, and confidence in technological reliability. These behavioural and organizational factors may significantly influence employees' willingness to utilize intelligent supply chain systems in operational contexts.

Within manufacturing firms, SSCM adoption decisions are typically guided by structured implementation processes and supported by institutional governance mechanisms. As such, adoption behaviour may be shaped by organizational readiness, perceived system effectiveness, and trust in technological performance rather than by individual attitudes alone. Understanding these determinants is essential in explaining how manufacturing organizations respond to the integration of AI-enabled supply chain technologies and how such perceptions translate into sustained system usage behaviour.

The Role of Perceived Risk in Technology Adoption

Perceived risk has been widely recognized as a potential barrier to technology adoption in both consumer and organizational information systems research. Previous studies have identified several dimensions of perceived risk, including performance risk, financial risk, privacy risk, and security risk, which may negatively influence users' willingness to adopt new technological systems. Perceived uncertainty regarding system reliability or implementation costs may therefore reduce user confidence in technology utilization.

In institutionalized B2B manufacturing environments, risk associated with technological implementation is often redistributed and absorbed through governance mechanisms, contractual agreements, and structured oversight committees. Institutional theory posits that organizational behaviour is shaped by regulative, normative, and cognitive structures that reduce uncertainty through standardized practices. Within such contexts, risk is not evaluated solely at the individual cognitive level but is embedded within organizational control systems. This suggests that perceived technological risk may be attenuated through formal safeguards, thereby reducing its behavioural impact on system usage decisions.

However, in professional environments such as manufacturing supply chains, risks associated with technology implementation are often managed through formal organizational mechanisms, including vendor agreements, implementation policies, and risk mitigation strategies. These institutional practices may reduce the influence of individual perceptions of technological risk on SSCM system usage behaviour. Consequently, the effect of perceived risk on SSCM adoption within manufacturing firms may be less pronounced compared to consumer-oriented technology adoption contexts, thereby highlighting the importance of examining other behavioural determinants influencing usage behaviour.

Hypothesis Development

Technology adoption models such as the Unified Theory of Acceptance and Use of Technology (UTAUT2) emphasize the importance of usability perceptions in influencing system acceptance. Effort Expectancy (EE) reflects the perceived ease of use associated with technological systems, which may facilitate user acceptance by reducing implementation complexity and required training efforts. Systems that are perceived as intuitive and user-friendly are more likely to be accepted by operational personnel within manufacturing organizations.

Technology Readiness (TR) represents the organizational capability to implement and utilize technological systems effectively. Firms that possess adequate infrastructure support, skilled personnel, and implementation experience may demonstrate greater readiness to integrate SSCM systems into operational processes. Organizational preparedness may therefore contribute positively to SSCM system usage behaviour.

Trust (T) refers to users' confidence in the reliability and effectiveness of intelligent technological systems. In manufacturing environments, trust in system performance may influence employees' willingness to utilize AI-enabled SSCM platforms in operational decision-making processes. Higher levels of perceived trust may enhance acceptance and encourage sustained system usage behaviour.

Conversely, Perceived Risk (PR) may negatively influence technology adoption by increasing uncertainty regarding system performance and implementation outcomes. However, in organizational environments where risk management practices are institutionalized, the influence of perceived risk on SSCM system usage behaviour may be reduced due to the presence of formal governance mechanisms and implementation safeguards.

In addition to explanatory modelling, predictive modelling techniques have increasingly been applied in technology adoption research to evaluate the predictive capability of behavioural determinants on system usage outcomes. Artificial intelligence (AI)-based models such as Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) are capable of capturing nonlinear relationships among adoption-related constructs. Therefore, it is expected that Effort Expectancy, Technology Readiness, Trust, and Perceived Risk may collectively contribute to the prediction of SSCM system usage behaviour.

Based on the above arguments, the following hypotheses are proposed:

H1: Effort Expectancy has a significant positive effect on SSCM system usage behaviour.

H2: Technology Readiness has a significant positive effect on SSCM system usage behaviour.

H3: Trust has a significant positive effect on SSCM system usage behaviour.

H4: Perceived Risk has a significant negative effect on SSCM system usage behaviour.

H5: AI-based predictive models can accurately predict SSCM system usage behaviour using Effort Expectancy, Technology Readiness, Trust, and Perceived Risk as input variables.

METHODOLOGY

Data Collection and Sampling Technique

This study adopts a quantitative cross-sectional survey design to examine the determinants influencing the adoption of Artificial Intelligence (AI)-enabled Smart Supply Chain Management (SSCM) systems among manufacturing firms in Malaysia. A purposive sampling technique was employed to ensure that respondents possessed relevant experience in supply chain operations, technology implementation, or organizational decision-making processes within manufacturing environments.

A total of 500 structured questionnaires were distributed to professionals working in manufacturing organizations across various industry sub-sectors. Out of the distributed questionnaires, 308 valid responses were

received and used for further analysis, representing a response rate of 61.6%. The respondents consisted of supply chain managers, logistics executives, operations managers, IT personnel, and procurement officers who were directly involved in SSCM-related processes.

The participating firms varied in size, including small and medium-sized enterprises as well as large manufacturing organizations operating in sectors such as electronics, automotive, food processing, and industrial manufacturing. The professional involvement of respondents ensured the contextual relevance of the collected data for assessing SSCM system usage behaviour.

Measurement of Constructs

All constructs included in this study were measured using multiple-item scales adapted from established technology adoption literature. Effort Expectancy items were adapted from Venkatesh et al. (2012), while Technology Readiness was measured based on the Technology Readiness Index developed by Parasuraman (2000). Trust-related items were adapted from Gefen et al. (2003) and McKnight et al. (2002), whereas Perceived Risk items were adapted from Featherman and Pavlou (2003).

All measurement items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). SSCM system Usage Behaviour was measured based on respondents' reported frequency of system utilization in operational supply chain decision-making processes.

Measurement Model Evaluation

The measurement model was evaluated using Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess the reliability and validity of the constructs included in the proposed research framework. Internal consistency reliability was examined using Cronbach's Alpha and Composite Reliability values. All constructs exceeded the recommended reliability threshold of 0.70, indicating satisfactory internal consistency.

Convergent validity was assessed using the Average Variance Extracted (AVE) values, which exceeded the minimum threshold of 0.50 for all constructs. Discriminant validity was evaluated using the Fornell-Larcker criterion, which confirmed that the square root of AVE for each construct was greater than its correlations with other constructs.

Common Method Bias Assessment

Given that the study relies on self-reported survey data, both procedural and statistical remedies were applied to mitigate potential common method bias. Procedurally, respondent anonymity was assured, and item wording was refined to reduce ambiguity and evaluation apprehension. Statistically, Harman's single-factor test was conducted using exploratory factor analysis. The first unrotated factor accounted for 34.2% of the total variance, which is below the 50% threshold commonly used to indicate serious common method bias. These results suggest that common method bias does not pose a significant threat to the validity of the findings.

Structural Model Assessment

The structural relationships among Effort Expectancy (EE), Technology Readiness (TR), Trust (T), Perceived Risk (PR), and SSCM system Usage Behaviour (UB) were examined using PLS-SEM. This approach was selected due to its suitability for predictive and exploratory research models involving multiple latent constructs. The structural model was evaluated based on path coefficients, coefficient of determination (R^2), and predictive relevance (Q^2) value

AI-Based Predictive Modelling

To enhance predictive rigor, the dataset was randomly divided into training (70%) and testing (30%) subsets. Model performance was evaluated on unseen test data to ensure out-of-sample validation. For the XGBoost model, hyperparameters including learning rate, maximum tree depth, and number of estimators were optimized using grid search with 5-fold cross-validation. Early stopping criteria were applied to prevent overfitting.

Similarly, the ANN model was implemented using a feedforward multilayer perceptron architecture. The model was trained using 5-fold cross-validation with dropout regularization (0.2 rate) applied between hidden layers to mitigate overfitting risk. The Adam optimizer was employed with a learning rate of 0.001. Model performance was evaluated using R^2 , RMSE, and Mean Absolute Error (MAE) on the test dataset.

RESULTS

Descriptive Statistics

Table 1 presents the descriptive statistics for the study constructs, including Effort Expectancy (EE), Technology Readiness (TR), Trust (T), Perceived Risk (PR), and SSCM system Usage Behaviour (UB). The results indicate that respondents generally reported moderate to high levels of Effort Expectancy, Technology Readiness, Trust, and SSCM system usage behaviour.

Table 1: Descriptive Statistics of Study Constructs

Construct	Mean	Standard Deviation
Effort Expectancy (EE)	3.84	0.67
Technology Readiness (TR)	3.76	0.71
Trust (T)	3.91	0.63
Perceived Risk (PR)	2.98	0.74
Usage Behaviour (UB)	3.88	0.69

Structural Model Evaluation

The structural model was assessed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the relationships between Effort Expectancy (EE), Technology Readiness (TR), Trust (T), Perceived Risk (PR), and SSCM system Usage Behaviour (UB). The path coefficient results indicate that Effort Expectancy has a significant positive effect on SSCM system usage behaviour ($\beta = 0.224$, $p = 0.001$), thus supporting H1. Similarly, Technology Readiness demonstrates a significant positive influence on SSCM system usage behaviour ($\beta = 0.218$, $p = 0.006$), providing support for H2. Trust is also found to significantly influence SSCM system usage behaviour ($\beta = 0.151$, $p = 0.017$), thereby supporting H3.

However, the effect of Perceived Risk on SSCM system usage behaviour is not statistically significant ($\beta = 0.086$, $p = 0.143$). Therefore, H4 is not supported. Although theory predicts a negative relationship between perceived uncertainty and technology usage, the findings suggest that perceived risk does not function as a decisive deterrent in institutionalized manufacturing environments. This suggests that other drivers, such as Technology Readiness and Trust, carry significantly more weight in the decision-making process of manufacturing firms

These findings suggest that usability, organizational readiness, and trust play more substantial roles in influencing SSCM system usage behaviour compared to perceived technological risk within manufacturing environments.

Predictive Relevance of the Structural Model

The predictive relevance of the structural model was evaluated using the Stone–Geisser’s Q^2 predict value. The Q^2 predict value for SSCM system usage behaviour was recorded at 0.284, indicating satisfactory predictive relevance of the model. This result suggests that the independent variables included in the model demonstrate

adequate predictive capability in explaining SSCM system usage behaviour among Malaysian manufacturing firms.

AI-Based Predictive Analysis

To complement the explanatory findings obtained through Partial Least Squares Structural Equation Modelling (PLS-SEM), artificial intelligence (AI)-based predictive models were developed to evaluate the predictive capability of Effort Expectancy (EE), Technology Readiness (TR), Trust (T), and Perceived Risk (PR) on SSCM system Usage Behaviour (UB).

Two predictive modelling approaches were implemented, namely Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN). The performance of the predictive models was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and classification accuracy. The results are presented in Table 2.

Table 2: Performance of AI-Based Predictive Models

Model	R^2	RMSE	Accuracy (%)
XGBoost	0.742	0.298	83.7
ANN	0.769	0.285	85.2

The results indicate that both predictive models achieved high levels of accuracy in predicting SSCM system usage behaviour, with the ANN model slightly outperforming the XGBoost model in terms of R^2 and RMSE values. These findings support H5 and suggest that behavioural determinants such as usability, organizational readiness, and trust contribute substantially to the prediction of SSCM system usage behaviour, whereas perceived risk demonstrates a comparatively minimal contribution.

Table 3 presents the relative feature importance scores obtained from the XGBoost model in predicting SSCM system usage behaviour based on the survey responses collected from 308 Malaysian manufacturing firms.

Table 3: Feature Importance Based on XGBoost Model

Predictor	Importance Score
Technology Readiness (TR)	0.36
Effort Expectancy (EE)	0.29
Trust (T)	0.24
Perceived Risk (PR)	0.11

The results indicate that Technology Readiness contributes most substantially to the prediction of SSCM system usage behaviour, followed by Effort Expectancy and Trust. In contrast, Perceived Risk demonstrates the lowest relative contribution among the predictors. This finding is consistent with the structural model results, which indicate that Perceived Risk does not significantly influence SSCM system usage behaviour.

Figure 1 illustrates the relative importance of Effort Expectancy, Technology Readiness, Trust, and Perceived Risk in predicting SSCM system usage behaviour using the XGBoost model.

Figure 1: Relative Feature Importance of Predictors Based on XGBoost Model

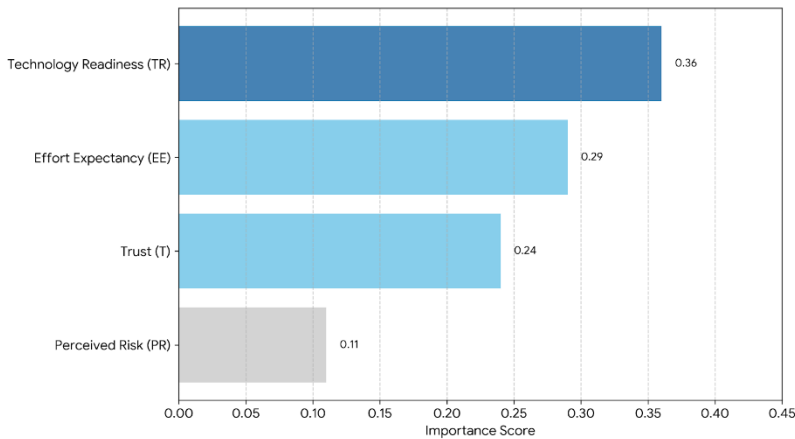


Figure 1: Relative Feature Importance of Predictors Based on XGBoost Model

Figure 2 presents the relationship between observed and predicted SSCM system usage behaviour based on the ANN and XGBoost models. The close alignment of predicted values with the reference line indicates satisfactory predictive performance of both models in estimating SSCM system usage behaviour among Malaysian manufacturing firms.

Figure 2: Observed versus Predicted SSCM System Usage Behaviour Based on AI Models

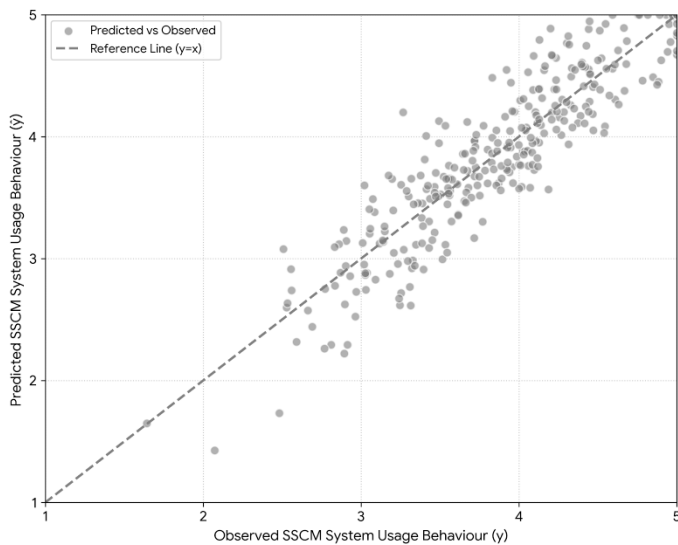


Figure 2: Observed versus Predicted SSCM System Usage Behaviour Based on AI Models

To assess the predictive power of the proposed model, the study employed a dual-model AI approach. Figure 1 illustrates the relative feature importance derived from the XGBoost algorithm, identifying Technology Readiness (0.36) and Effort Expectancy (0.29) as the primary determinants of usage. Furthermore, the predictive accuracy was validated through a comparison of observed versus predicted values (Figure 2). The high degree of alignment along the 45-degree reference line ($y = x$) and the high coefficient of determination ($R^2 = 0.769$) confirm the model's robustness in predicting AI-enabled SSCM adoption within the Malaysian manufacturing context.

DISCUSSION

The findings of this study indicate that Effort Expectancy, Technology Readiness, and Trust significantly influence the usage behaviour of AI-enabled Smart Supply Chain Management (SSCM) systems within manufacturing organizations. These results suggest that organizational readiness and perceived usability play a more prominent role in shaping adoption decisions compared to individual perceptions of technological risk. In

operational environments where supply chain decisions involve collective responsibility and institutional oversight, usability and preparedness may facilitate system acceptance by reducing implementation complexity and increasing confidence in technological integration.

The non-significant effect of Perceived Risk can be theoretically interpreted through institutional theory and organizational risk absorption perspectives. In highly institutionalized B2B manufacturing environments, technology adoption decisions are embedded within formal governance frameworks, contractual safeguards, and compliance structures. These institutional mechanisms redistribute and absorb technological uncertainty at the organizational level, thereby reducing the salience of individual risk perceptions.

From a risk absorption perspective, firms internalize technological uncertainty through pilot implementation phases, structured evaluation committees, financial buffering strategies, and vendor accountability mechanisms. Consequently, perceived risk does not directly translate into reduced usage behaviour because risk is collectively managed rather than individually borne.

This finding extends technology adoption theory by identifying a contextual boundary condition of Perceived Risk. While prior consumer-oriented studies consistently report negative effects of risk on adoption behaviour, the present results suggest that in governance-intensive B2B environments, institutional safeguards attenuate its behavioural influence. Thus, adoption theory must account for structurally embedded contexts in which risk perceptions are neutralized through organizational mechanisms.

Furthermore, the significant influence of Trust and Technology Readiness highlights the importance of organizational preparedness in facilitating SSCM adoption. Firms that invest in workforce capability development, infrastructure support, and implementation training may experience higher levels of system acceptance among operational personnel. Trust in the reliability and performance of intelligent supply chain systems may also strengthen user confidence, thereby supporting sustained usage behaviour in operational processes.

The predictive analyses conducted using XGBoost and Artificial Neural Networks further reinforce the importance of usability, readiness, and trust as dominant contributors to SSCM system usage behaviour. The minimal contribution of Perceived Risk in the predictive models suggests that adoption challenges in professional supply chain environments may be more closely associated with implementation complexity and organizational preparedness than with perceived technological threats.

CONCLUSION

This study advances technology adoption theory by identifying an institutional boundary condition of Perceived Risk within AI-enabled supply chain environments. Whereas traditional UTAUT-based research conceptualizes perceived risk as a universal inhibitor of technology usage, the present findings demonstrate that in governance-intensive B2B manufacturing contexts, institutional safeguards and organizational risk absorption mechanisms attenuate its behavioural effect. This theoretical refinement shifts the focus of adoption research from purely individual cognitive evaluations toward structurally embedded organizational contexts. Methodologically, the integration of PLS-SEM with cross-validated AI-based predictive modelling further strengthens the robustness and practical relevance of the findings.

From a practical perspective, the results provide useful insights for managers and practitioners seeking to support the integration of AI-enabled SSCM technologies within manufacturing organizations. Emphasis on workforce readiness, implementation support, and user-friendly system design may enhance acceptance and sustained system usage among operational personnel. Future research may consider examining additional organizational or environmental factors that influence SSCM adoption across different industrial contexts.

ACKNOWLEDGEMENTS

The authors would like to express their sincere appreciation to all respondents from the Malaysian manufacturing sector who participated in this study and provided valuable insights for the research. The authors also

acknowledge the academic support and institutional assistance provided by Universiti Teknikal Malaysia Melaka (UTeM) throughout the completion of this study.

REFERENCES

1. C. Cagliano, G. Mangano, and C. Rafele, "Determinants of digital technology adoption in supply chain. An exploratory analysis," *Supply Chain Forum: An Int. J.*, vol. 22, no. 4, pp. 337–351, 2021, doi: 10.1080/16258312.2021.1973312.
2. Hasija and T. L. Esper, "In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance," *J. Bus. Logist.*, vol. 43, no. 1, pp. 133–158, 2022, doi: 10.1111/jbl.12292.
3. K. Bhardwaj, A. Garg, and A. G. Garg, "Determinants of blockchain technology adoption in supply chains by small and medium enterprises (SMEs) in India," *Math. Probl. Eng.*, vol. 2021, p. 5534035, 2021, doi: 10.1155/2021/5534035.
4. Rijanto, "Blockchain technology adoption in supply chain finance," *J. Theor. Appl. Electron. Commer. Res.*, vol. 16, no. 7, pp. 3078–3098, 2021, doi: 10.3390/jtaer16070168.
5. Ageron, O. Bentahar, and R. Gunasekaran, "Digital supply chain: challenges and future directions," *Supply Chain Forum: An Int. J.*, vol. 21, no. 3, pp. 133–138, 2020, doi: 10.1080/16258312.2020.1816361.
6. Giua, V. C. Materia, and L. Camanzi, "Smart farming technologies adoption: Which factors play a role in the digital transition?," *Technol. Soc.*, vol. 68, p. 101869, 2022, doi: 10.1016/j.techsoc.2022.101869.
7. T. Nguyen, T. T. Nguyen, L. Cai, K. F. Yuen, and X. Wang, "A perception-based investigation on logistics robot adoption: from an integrated perspective of trust formation and technology acceptance," *Int. J. Logist. Res. Appl.*, vol. 28, no. 1, pp. 89–112, 2025, doi: 10.1080/13675567.2024.2346265.
8. Loske and M. Klumpp, "Intelligent and efficient? An empirical analysis of human–AI collaboration for truck drivers in retail logistics," *Int. J. Logist. Manag.*, vol. 32, no. 4, pp. 1344–1367, 2021, doi: 10.1108/IJLM-03-2020-0145.
9. D. Rico-Bautista, C. D. Guerrero, and C. A. Collazos-Morales, "Smart University: A vision of technology adoption," *Revista Colombiana de Computación*, vol. 22, no. 1, pp. 13–25, 2021, doi: 10.29375/25392115.4214.
10. Weisz, D. M. Herold, N. K. Ostern, R. Payne, and S. M. Wagner, "Artificial intelligence (AI) for supply chain collaboration: implications on information sharing and trust," *Online Inf. Rev.*, vol. 49, no. 2, pp. 321–340, 2025, doi: 10.1108/OIR-04-2024-0205.
11. Jain, H. Singh, K. R. Chaturvedi, and S. Rakesh, "Blockchain in logistics industry: in fizza customer trust or not," *J. Enterp. Inf. Manag.*, vol. 33, no. 3, pp. 541–558, 2020, doi: 10.1108/JEIM-01-2019-0004.
12. Malhotra and M. Kharub, "Elevating logistics performance: harnessing the power of artificial intelligence in e-commerce," *Int. J. Logist. Manag.*, vol. 36, no. 1, pp. 234–256, 2025, doi: 10.1108/IJLM-05-2023-0201.
13. G. Zhang, Y. Yang, and G. Yang, "Smart supply chain management in Industry 4.0: the review, research agenda and strategies in North America," *Ann. Oper. Res.*, vol. 322, pp. 1075–1117, 2023, doi: 10.1007/s10479-021-04490-6.
14. G. Sahebi, B. Masoomi, and S. Ghorbani, "Expert oriented approach for analyzing the blockchain adoption barriers in humanitarian supply chain," *Technol. Soc.*, vol. 63, p. 101427, 2020, doi: 10.1016/j.techsoc.2020.101427.
15. Paliszkievicz and J. Gołuchowski, "Trust and artificial intelligence," in *Trust and Application of AI in Industry 5.0*, Boca Raton, FL: CRC Press, 2024, pp. 1–16.
16. L. Lee, S. Y. Wong, H. M. Alzoubi, and M. Alshurideh, "Adopting smart supply chain and smart technologies to improve operational performance in manufacturing industry," *Int. J. Innov. Sci.*, vol. 15, no. 5, pp. 837–857, 2023, doi: 10.1108/IJIS-07-2022-0125.
17. W. Wong, G. W. H. Tan, V. H. Lee, K. B. Ooi, and A. K. L. Soh, "Unearthing the determinants of Blockchain adoption in supply chain management," *Int. J. Prod. Res.*, vol. 59, no. 11, pp. 3336–3353, 2021, doi: 10.1080/00207543.2020.1861317.
18. Alazab, S. Alhyari, A. Awajan, and A. B. Abdallah, "Blockchain technology in supply chain management: an empirical study of the factors affecting user adoption/acceptance," *Cluster Comput.*, vol. 24, no. 1, pp. 83–101, 2021, doi: 10.1007/s10586-020-03200-4.

19. Jain, G. Soni, D. Verma, R. Baraiya, and B. Ramtiyal, "Selection of technology acceptance model for adoption of industry 4.0 technologies in agri-fresh supply chain," *Sustainability*, vol. 15, no. 4, p. 3769, 2023, doi: 10.3390/su15043769.
20. Ullah, W. M. Al-Rahmi, A. I. Alzahrani, O. Alfarraj, and F. Alblehai, "Blockchain technology adoption in smart learning environments," *Sustainability*, vol. 13, no. 4, p. 1801, 2021, doi: 10.3390/su13041801.
21. B. Babatunde, C. T. Okonji, and A. O. Adekunle, "Public-Private Partnerships in Advancing AI-Based Logistics," *NIU J. Soc. Sci.*, vol. 1, no. 1, pp. 45–58, 2025.
22. Kahr, G. Rooks, C. Snijders, and M. van der Aalst, "Good Performance Isn't Enough to Trust AI: Lessons from Logistics Experts on their Long-Term Collaboration with an AI Planning System," in *Proc. 2025 CHI Conf. Hum. Factors Comput. Syst.*, New York, NY, USA, 2025, pp. 1–15, doi: 10.1145/xxxxxxx.xxxxxx.
23. D. Raut, A. Gotmare, B. E. Narkhede, S. J. Govindarajan, and P. R. J., "Enabling technologies for Industry 4.0 manufacturing and supply chain: concepts, current status, and adoption challenges," *IEEE Eng. Manag. Rev.*, vol. 48, no. 2, pp. 83–102, 2020, doi: 10.1109/EMR.2020.2987874.
24. G. Richey Jr, S. Chowdhury, M. S. Davis-Sramek, A. Giannakis, and D. A. Whipple, "Artificial intelligence in logistics and supply chain management: A primer and roadmap for research," *J. Bus. Logist.*, vol. 44, no. 4, pp. 532–549, 2023, doi: 10.1111/jbl.12364.
25. A. R. Khan, Z. Ahmad, A. A. Sheikh, and Y. Yu, "Digital transformation, smart technologies, and eco-innovation are paving the way toward sustainable supply chain performance," *Sci. Prog.*, vol. 105, no. 3, p. 00368504221120147, 2022, doi: 10.1177/00368504221120147.
26. S. Bag, D. A. Viktorovich, A. K. Sahu, and M. Shankar, "Barriers to adoption of blockchain technology in green supply chain management," *J. Glob. Oper. Strateg. Sourc.*, vol. 14, no. 1, pp. 104–133, 2021, doi: 10.1108/JGOSS-05-2020-0027.
27. S. Chowdhury, O. Rodriguez-Espindola, P. Dey, and S. K. Budhwar, "Blockchain technology adoption for managing risks in operations and supply chain management: evidence from the UK," *Ann. Oper. Res.*, vol. 327, pp. 539–577, 2023, doi: 10.1007/s10479-021-04490-6.
28. S. Saurabh and K. Dey, "Blockchain technology adoption, architecture, and sustainable agri-food supply chains," *J. Clean. Prod.*, vol. 284, p. 124731, 2021, doi: 10.1016/j.jclepro.2020.124731.
29. S. Yousefi and B. M. Tosarkani, "An analytical approach for evaluating the impact of blockchain technology on sustainable supply chain performance," *Int. J. Prod. Econ.*, vol. 246, p. 108429, 2022, doi: 10.1016/j.ijpe.2022.108429.
30. Mitra, R. Kapoor, and N. Gupta, "Studying key antecedents of disruptive technology adoption in the digital supply chain: an Indian perspective," *Int. J. Emerg. Mark.*, vol. 18, no. 12, pp. 5993–6015, 2023, doi: 10.1108/IJOEM-08-2021-1315.