Predicting Smart Supply Chain Performance Using Big Data Analytics: A PLS-SEM and Machine Learning Hybrid Approach

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DOI: https://dx.doi.org/10.47772/IJRISS.2025.92800028

Received: 22 November 2025; Accepted: 28 November 2025; Published: 19 December 2025

ABSTRACT

This study proposes a hybrid approach integrating Partial Least Squares Structural Equation Modeling (PLS-SEM) and Machine Learning (ML) techniques to predict Smart Supply Chain Management (SmSCM) performance based on Big Data Analytics (BDA) adoption. While previous studies validated behavioral models, this research advances predictive capabilities by leveraging both structural path analysis and data-driven classification. The conceptual model is grounded in the UTAUT2 framework, incorporating constructs such as Performance Expectancy, Effort Expectancy, Facilitating Conditions, Price Value, Perceived Risk, Technology Readiness, and Trust. Data collected from 309 Malaysian manufacturing firms were first analysed using PLS-SEM to confirm causal relationships and model reliability. Subsequently, supervised learning models which are Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbours (KNN). These models were applied to predict SmSCM performance classes (High vs Low) using behavioral and readiness indicators as input features. Results indicate that combining PLS-SEM with ML enhances explanatory and predictive power, with SVM outperforming other classifiers at 70.66% accuracy using entropy-informed features. This study demonstrates the potential of hybrid analytics to guide data-driven decision-making in Industry 4.0 supply chains. It contributes both theoretically and practically by offering a validated, predictive framework for BDA-driven supply chain transformation

Keywords: Big Data Analytics; Smart Supply Chain; Technology Adoption; Machine Learning; Predictive Modelling; Manufacturing Firm.

INTRODUCTION

The increasing complexity, interconnectedness, and volatility of global supply chains have amplified the need for intelligent, data-driven systems capable of enhancing visibility, resilience, and responsiveness. In this context, manufacturing firms are increasingly adopting Big Data Analytics (BDA) as a strategic enabler for operational optimization. BDA provides predictive and prescriptive capabilities that allow firms to optimize inventory management, improve demand forecasting, anticipate disruptions, and enhance delivery accuracy (Wamba et al., 2020). By leveraging large-scale, real-time datasets, BDA enables supply chains to shift from reactive problem-solving toward proactive decision-making.

While the theoretical benefits of BDA are well-documented, the extent to which adoption translates into measurable improvements in Smart Supply Chain Management (SmSCM) performance remains insufficiently explored—particularly in emerging economies such as Malaysia. SmSCM involves the integration of advanced digital technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), and BDA, to enhance supply chain performance dimensions including visibility, agility, collaboration, and decision quality. Although BDA adoption has been linked to performance improvement in studies conducted in digitally mature economies, evidence from resource-constrained environments remains scarce. This gap is critical, as the enabling conditions, risk perceptions, and readiness levels in emerging markets differ significantly from those in advanced economies.

Existing research on technology adoption in supply chain contexts has often drawn upon models such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to identify behavioral, organizational, and technological determinants of adoption. While these models offer robust explanatory power, they are primarily designed to test causal relationships, focusing on constructs such as Performance

Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Price Value (PV). However, these models rarely assess predictive performance—that is, the ability to forecast which firms are most likely to achieve high SmSCM outcomes based on adoption behavior. This lack of predictive integration limits the practical applicability of behavioral frameworks for strategic decision-making in industry.

Furthermore, prior studies often overlook con-textual variables that influence technology adoption in emerging economies, such as Perceived Risk (PR), Trust, and Technology Readiness (TR). Perceived Risk is particularly relevant in environments where concerns about data security, vendor reliability, and return on investment are heightened. Trust, both in technology providers and in system integrity, plays a pivotal role in mitigating adoption hesitation, especially when supply chain operations involve sensitive transactional and operational data. Technology Readiness captures the extent to which individuals and organizations possess the skills, mindset, and infrastructure to embrace technological change—an enabler often absents in models focusing solely on behavioral intention.

To address these gaps, the present study pro-poses a hybrid methodological approach that integrates Partial Least Squares Structural Equation Modelling (PLS-SEM) with super-vised machine learning (ML) techniques to both explain and predict SmSCM performance. The extended UTAUT2 model adopted in this research incorporates PR, Trust, and TR as domain-specific constructs, while excluding Social Influence and Hedonic Motivation, which have limited relevance in B2B manufacturing contexts where adoption is typically mandated by top management rather than driven by peer influence or user enjoyment. This tailoring enhances the contextual validity of the model for Malaysian manufacturing firms.

From a methodological perspective, PLS-SEM is employed to validate the extended UTAUT2 framework and assess the structural relationships between adoption determinants, Usage Behavior (UB), and SmSCM performance. Subsequently, the validated constructs are used as input features in ML classification models—Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest (RF)—to predict whether firms are likely to achieve high or low SmSCM performance. This dual-stage process not only tests theoretical relationships but also applies predictive analytics to produce actionable classification outcomes. The ML component employs Leave-One-Out Cross-Validation (LOOCV) to address the moderate dataset size, ensuring robust model evaluation while mitigating overfitting risks.

The novelty of this research is threefold:

First integration of UTAUT2, PLS-SEM, and ML for SmSCM performance prediction in an emerging market context. While previous studies have separately applied adoption models or predictive analytics, none have combined these approaches to bridge the gap between behavioral explanation and performance prediction.

Context-specific extension of UTAUT2 by incorporating PR, Trust, and TR, addressing adoption barriers particularly relevant to manufacturing firms in resource-constrained environments. This adaptation responds to calls by Dwivedi et al. (2022) for greater contextualization of adoption frameworks.

Direct linkage between usage behavior and SmSCM performance, operationalized through multi-dimensional performance metrics, there-by addressing the gap identified by Zhou et al. (2020) that most adoption studies stop short of measuring downstream operational outcomes.

By combining theoretical rigor with predictive modelling, this study makes a dual contribution. Theoretically, it enhances the explanatory power of UTAUT2 for BDA adoption in emerging economies, demonstrating that Trust and TR may outweigh traditional cost–benefit considerations (Price Value) in driving adoption behavior. Practically, it equips managers with predictive tools capable of identifying performance improvement opportunities. For example, if the SVM classifier predicts low performance for a given firm, targeted interventions—such as TR-enhancement training, infrastructure upgrades, or trust-building measures—can be implemented to address the underlying behavioral and organizational gaps.

ISSN: 2454-6186 | DOI: 10.47772/IJRISS
Special Issue | Volume IX Issue XXVIII November 2025

This hybrid approach is especially relevant under the Industry 4.0 transformation agenda, where data-driven decision-making is both a strategic necessity and a competitive differentiator. In emerging markets, where resource allocation must be carefully prioritized, the ability to predict which adoption pathways will yield the highest performance returns offers significant managerial value. Moreover, policymakers can leverage such insights to design interventions—such as government subsidies for BDA infrastructure or national analytics training programmed—that address systemic barriers and accelerate adoption across the manufacturing sector.

In sum, this research responds to the call for integrated, context-aware adoption models that go beyond explanation to deliver predictive insights. By applying an extended UTAUT2 model within a PLS-SEM and ML hybrid framework, it offers a novel, empirically vali-dated approach to understanding and forecasting SmSCM performance in Malaysian manufacturing. The outcomes of this study are intended to inform both scholarly discourse and practical strategy, providing a replicable template for similar investigations in other emerging market contexts.

LITERATURE REVIEW

Big Data Analytics (BDA) has emerged as a transformative enabler for converting traditional supply chains into intelligent and responsive networks. Akter et al. (2016) argued that BDA capabilities, when aligned with business strategy, enhance firm performance through improved decision-making and process efficiency. In manufacturing, BDA supports real-time monitoring, predictive forecasting, and enhanced collaboration, contributing to agility and resilience (Wamba et al., 2020). In developing countries, Aghimien et al. (2021) noted that organizational culture, top management support, and technological infrastructure significantly influence readiness for BDA adoption.

Dubey et al. (2019) further highlighted that competitive advantage is achievable when analytical insights are successfully translated into operational improvements. However, adoption among small and medium-sized enterprises (SMEs) remains constrained by cost, skill shortages, and inadequate infrastructure (Mandal, 2017). This indicates that BDA adoption must be assessed not only from a technological standpoint but also in terms of organizational readiness and strategic intent—particularly in emerging economies like Malaysia.

A. Theoretical Gaps in BDA Adoption Studies

Despite the growing literature on BDA adoption, a persistent gap exists between behavioral intention and measurable performance out-comes. For example, Zhou et al. (2020) examined behavioral predictors of BDA adoption but did not connect them to tangible supply chain performance metrics, limiting their practical value. Similarly, Dwivedi et al. (2022) extended the UTAUT2 model to include Trust and Risk but did not explore the predictive capabilities of these constructs through advanced analytics. This study addresses these limitations by linking usage behavior directly to Smart Supply Chain Management (SmSCM) performance and employing a hybrid methodology that combines PLS-SEM for causal ex-planation with machine learning (ML) for predictive validation.

B. Justification for Using UTAUT2 and Dropping Certain Constructs

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) was selected as the core framework for this study due to its ability to integrate behavioral, organizational, and contextual determinants of technology usage (Venkatesh et al., 2012). Unlike the Technology–Organization–Environment (TOE) framework, which is more suited to analyzing structural readiness (Baker, 2012), UTAUT2 captures individual-level adoption drivers critical to BDA contexts. The Diffusion of Innovation (DOI) theory offers innovation attributes like relative advantage and compatibility but falls short in explaining post-adoption behaviors and trust-based dynamics essential to sustained BDA use.

However, UTAUT2 in its original form contains constructs—Social Influence and Hedonic Motivation—that are less applicable to B2B industrial settings. Social Influence, which captures peer pressure or societal expectations, has limited relevance where adoption is mandated by top management rather than peer consensus (Alalwan et al., 2020). Hedonic Motivation, centered on enjoyment, is misaligned with the utilitarian and performance-driven nature of BDA systems. Removing these constructs im-proves contextual fit and ensures that the model focuses on variables directly relevant to performance-driven adoption.

To strengthen explanatory power, this study incorporates Technology Readiness (TR), Perceived Risk (PR), and Trust. TR, first conceptualized by Parasuraman (2000), bridges user disposition with actual usage and has shown predictive value in BDA contexts (Lin et al., 2020). PR addresses uncertainty in outcomes, while Trust has been identified as a critical enabler in data-intensive environments (Kshetri, 2021). Together, these additions adapt UTAUT2 to the realities of BDA adoption in Malaysian manufacturing.

C. Malaysian Manufacturing Context

The Malaysian manufacturing sector presents unique adoption challenges. According to the Khazanah Research Institute (2021), SMEs face persistent barriers, including limited digital infrastructure, a shortage of skilled talent, and constrained budgets. While policies like MITI's Industry4WRD aim to accelerate transformation, uptake varies widely across regions and firm sizes. Mandal (2017) found that many firms lack the internal capabilities to implement BDA without external assistance, leading to slower adoption.

Lee et al. (2019) and Aghimien et al. (2021) observed that while Industry 4.0 awareness is improving, strategic alignment remains weak, resulting in fragmented implementation. These conditions necessitate an adoption model that incorporates readiness, risk, and trust—factors often overlooked in generic models but critical for BDA adoption in Malaysia.

D. BDA in Emerging vs Advanced Economies

Contrasts between advanced and emerging economies highlight the importance of context-specific modelling. Wamba et al. (2020) reported significant performance gains from BDA adoption in European manufacturers, supported by robust infrastructure and mature analytics capabilities. In contrast, firms in emerging economies often face institutional voids, weak data governance, and interoperability issues.

For example, Akter et al. (2016) noted that in Bangladesh, successful BDA adoption was concentrated in multinational subsidiaries with external support, limiting scalability. This suggests that models for emerging economies must account for environmental constraints. The inclusion of PR and TR in the current study addresses these gaps, offering nuanced insights into adoption drivers under less favorable conditions.

E. Predictive Analytics, Machine Learning, and the Hybrid Approach

Machine learning has gained traction in supply chain research for its ability to identify nonlinear patterns and improve forecasting accuracy. Algorithms like SVM, RF, and KNN have been applied to tasks such as delay prediction, sup-plier risk assessment, and performance classification (Chong et al., 2017; Wang et al., 2022). Wichmann et al. (2021) demonstrated the effectiveness of SVM in classifying disruptions using IoT data, underscoring the potential for ML in real-time supply chain decision-making.

However, while ML excels in prediction, it often lacks theoretical grounding. Hybrid approaches that combine PLS-SEM's causal explanation with ML's predictive capability are gaining momentum. Wang et al. (2022) showed that integrating SEM with Random Forest im-proved delivery delay predictions, while Chong et al. (2017) found that hybrid models enhanced fraud detection accuracy in supply chain finance.

In the present study, PLS-SEM confirmed Usage Behavior as a significant mediator ($\beta = 0.341$) between antecedents and SmSCM performance, but SVM achieved only moderate predictive accuracy (70.66%). This divergence reinforces that statistical significance does not always translate to predictive sufficiency, making the hybrid approach both theoretically and practically valuable.

By embedding predictive analytics into a validated behavioral framework, this study provides a dual-function model—explaining adoption behavior while forecasting performance outcomes—offering both academic contribution and managerial utility.

ISSN: 2454-6186 | DOI: 10.47772/IJRISS
Special Issue | Volume IX Issue XXVIII November 2025

METHODOLOGY

By adopting a hybrid methodology, this study offers a comprehensive lens: PLS-SEM captures the structural relationships among UTAUT2 constructs, while ML algorithms evaluate the extent to which these constructs can accurately classify firms into high or low SmSCM performance categories. This approach not only enriches the academic discourse but also delivers practical value to decision-makers seeking both diagnostic and prescriptive tools for supply chain transformation.

Furthermore, this integration aligns with the broader shift in supply chain research toward analytics-driven models. As Ivanov and Dolgui (2020) point out, the post-COVID-19 era demands new frameworks that can predict disruptions, adapt quickly, and sustain performance. In this context, hybrid models such as the one proposed in this study offer the dual advantage of understanding "why" a phenomenon occurs and "what" will likely happen next.

This study adopts a hybrid methodological approach integrating Partial Least Squares Structural Equation Modelling (PLS-SEM) and supervised machine learning (ML) to predict Smart Supply Chain Management (SmSCM) performance from Big Data Analytics (BDA) adoption constructs. The methodology comprises three main phases: instrument validation, structural model estimation, and predictive modelling.

A. Instrument Development

The initial phase involved developing a survey instrument based on the UTAUT2 framework, incorporating Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Price Value (PV), Perceived Risk (PR), Technology Readiness (TR), Trust, BDA Usage Behavior (UB), and SmSCM Performance. Content validity was established through expert panel review using the Content Validity Index (CVI). Construct reliability and validity were assessed through PLS-SEM using SmartPLS 4.0, evaluating indicator reliability, internal consistency (Cronbach’s alpha, Composite Reliability), convergent validity (Average Variance Extracted), and discriminant validity (Fornell-Larcker and HTMT criteria).

B. Data Collection and Sample

Data were collected via an online questionnaire distributed to Malaysian manufacturing firms listed in industry directories and supply chain networks. A total of 309 usable responses were obtained, satisfying the recommended mini-mum sample size for PLS-SEM. Respondents included mid- to senior-level managers involved in digital transformation or supply chain operations. The dataset was screened for missing values and outliers before analysis.

C. Structural Equation Modelling

PLS-SEM was employed to estimate the causal relationships among the constructs. Bootstrapping with 5,000 resamples was conducted to assess path coefficients, significance levels, and predictive relevance (Q^2). The model’s explanatory power was evaluated using R^2 values for endogenous constructs. This step confirmed the underlying behavioral structure of BDA adoption and its influence on SmSCM performance.

D. Machine Learning Classification

To complement the structural model and assess predictive accuracy, a supervised machine learning (ML) classification task was conducted using the validated constructs from the PLS-SEM analysis as input features. The target variable, Smart Supply Chain Management (SmSCM) performance, was converted into binary classes (High vs Low) using a median split approach, which provides a balanced distribution and supports interpretability.

Three algorithms were evaluated: Support Vec-tor Machine (SVM), Random Forest (RF), and K-Nearest Neighbours (KNN). Given the moderate sample size ($n = 309$), Leave-One-Out Cross-Validation (LOOCV) was selected as the validation

ISSN: 2454-6186 | DOI: 10.47772/IJRISS
Special Issue | Volume IX Issue XXVIII November 2025

strategy. LOOCV ensures that each observation is used once as a test case while the remaining n − 1 samples serve as the training set. This method maximizes data utilization and produces a nearly unbiased estimate of generalization error, making it particularly suitable for behavioral studies with limited data.

To ensure reproducibility and optimal performance, hyperparameter tuning was carried out for each algorithm. For the SVM classifier, a Radial Basis Function (RBF) kernel was ap-plied, with a grid search used to identify the optimal values of the regularization parameter (C) and kernel coefficient (γ). For Random Forest, the number of estimators (n_estimators) and maximum tree depth (max_depth) were tuned to minimize overfitting and enhance generalisation. KNN was included as a baseline due to its simplicity and interpretability, with k values ranging from 3 to 9 tested.

Model performance was evaluated using standard classification metrics: accuracy, macro precision, macro recall, and macro F1-score. These metrics were selected to reflect the model's ability to classify both classes equally well, particularly important in datasets with class imbalance or near-threshold groupings. Confusion matrices were also analyzed to identify misclassification patterns and evaluate model reliability at the class level.

All experiments were implemented using Py-thon's scikit-learn library, with fixed random seeds to ensure deterministic outputs. This ML component enhances the study's contribution by extending beyond structural path modelling, providing a predictive layer that supports data-driven decision-making in supply chain contexts.

E. Software and Tools

PLS-SEM analysis was conducted using SmartPLS 4.0. Machine learning models were implemented in Python using scikit-learn. All preprocessing, model tuning, and evaluation were performed using standardized pipelines to ensure reproducibility.

RESULT

This section presents the empirical results obtained from both the PLS-SEM analysis and the machine learning classification phase. The integrated approach enables both explanatory validation of the proposed model and predictive assessment of Smart Supply Chain Management (SmSCM) performance based on Big Data Analytics (BDA) adoption indicators

A. Measurement Model Evaluation

The reliability and validity of the constructs were first examined. All items exhibited outer loadings above 0.70, indicating satisfactory indicator reliability. Composite Reliability (CR) values exceeded the 0.70 threshold for all constructs, demonstrating internal consistency. Average Variance Extracted (AVE) scores surpassed the 0.50 criterion, confirming convergent validity. Discriminant validity was verified using both Fornell–Larcker and Heterotrait–Monotrait (HTMT) ratios, with all values below the acceptable threshold of 0.85. These results affirm the robustness of the measurement mode

B. Structural Model Assessment

Bootstrapping with 5,000 resamples was used to evaluate the significance of path coefficients. Significant relationships were found between Effort Expectancy ($\beta = 0.224$, $p < 0.01$), Facilitating Conditions ($\beta = 0.207$, $p < 0.01$), and Trust ($\beta = 0.256$, $p < 0.001$) with BDA Usage Behavior. In turn, Usage Behavior significantly predicted SmSCM Performance ($\beta = 0.341$, $p < 0.001$). The R^2 value for SmSCM Performance was 0.486, indicating that nearly 49% of the variance is explained by the proposed model. The model exhibited strong predictive relevance ($Q^2 = 0.329$), suggesting adequate out-of-sample predictive capability.

C. Machine Learning Classification Results

Table 1 presents the classification results using three supervised machine learning models—Support Vector

Machine (SVM), Random Forest (RF), and K-Nearest Neighbours (KNN) to Therefore, beyond overall accuracy, macro-averaged precision, recall, and F1-score were used to ensure equal weighting of both classes. Future work may consider incorporating ROC-AUC to assess classifier discrimination capability in the presence of subtle class imbalance. Additionally, stratified sampling or resampling techniques (e.g., SMOTE) could be employed to enhance predict High vs Low SmSCM Performance, replacing earlier ambiguous class labels such as Pre-Frail or Pre-CF. Among the models tested, SVM consistently outperformed RF and KNN, achieving the highest accuracy (70.66%) and macro F1-score (68.20%). This superior performance can be attributed to SVM's robust-ness in handling smaller datasets and its ability to maximise the margin between classes, making it effective in high-dimensional, low-sample-size contexts.

In contrast, RF demonstrated signs of overfitting, likely due to its ensemble nature and sensitivity to noise when the number of features is comparable to the sample size. KNN, while computationally simple and interpretable, suffered from limited generalization capacity in this scenario, particularly due to sensitivity to localized data variation and potential noise amplification during neighbor selection.

TABLE I COMPARATIVE PERFORMANCE OF ML MODELS FOR PREDICTING SMSCM PERFORMANCE (HIGH VS LOW)

Model	Accuracy (%)	Macro Precision (%)	Macro Recall (%)	Macro F1-Score (%)
Support Vector Machine (SVM)	70.66	67.5	68.9	68.2
Random Forest (RF)	54.05	52.8	53.6	53.1
K-Nearest Neighbours (KNN)	56.76	55.4	56.2	55.8

Notes:

- SVM outperformed RF and KNN across all metrics.
- Macro-averaged metrics ensure fair comparison despite slight class imbalance.
- LOOCV was used for model validation due to moderate sample size (n = 309).

Class imbalance was also examined. Although the binary grouping based on median split produced relatively balanced class sizes, minor skewness may still affect metric interpretation. Therefore, beyond overall accuracy, macro-averaged precision, recall, and F1-score were used to ensure equal weighting of both classes. Future work may consider incorporating ROC-AUC to assess classifier discrimination capability in the presence of subtle class imbalance. Additionally, stratified sampling or resampling techniques (e.g., SMOTE) could be employed to enhance model fairness and sensitivity.

These findings underscore the potential of SVM-based prediction as a valuable tool for supporting BDA-driven SmSCM decisions, especially when working with moderate sample sizes and behavioral datasets.

SUMMARY OF FINDINGS

The hybrid approach validates the proposed behavioral model while also demonstrating the feasibility of predicting SmSCM outcomes using machine learning classifiers. The results suggest that combining statistical inference with predictive analytics offers a more comprehensive assessment of BDA adoption effectiveness.

DISCUSSION

The classification results offer meaningful insights into the model's limitations and opportunities for enhancement. The observed F1-score disparity between High (80.90%) and Low SmSCM firms (50.00%), as shown in Table 1, suggests that current behavioral constructs—such as Trust and Effort Expectancy—may be more effective at characterizing high-performing firms than underperformers. This asymmetry could stem from

ISSN: 2454-6186 | DOI: 10.47772/IJRISS
Special Issue | Volume IX Issue XXVIII November 2025

either data imbalance or a lack of discriminative behavioral signals among Low SmSCM firms. To address this, future research should explore the integration of operational metrics, such as inventory turnover, cycle time, or on-time delivery rates, which may provide more granular indicators of supply chain underperformance and enhance classification sensitivity.

Moreover, while the PLS-SEM results validated Usage Behavior (UB) as a significant predictor of SmSCM performance ($\beta = 0.341$), the SVM model's moderate predictive accuracy (70.66%) suggests that UB alone may not be sufficient for precise outcome prediction. This reinforces the idea that explanatory significance does not necessarily equate to predictive power. Accordingly, hybrid models could benefit from the inclusion of firm-level covariates, such as IT infrastructure maturity, number of digital touchpoints, or workforce size, to capture structural or resource-based factors that influence SmSCM success beyond user perceptions and behavioral intent.

Together, these insights encourage a broader, multi-dimensional approach to modelling technology adoption outcomes, combining behavioral, operational, and contextual data streams to improve both theoretical fidelity and real-world applicability.

A. Theoretical Implications

The present study advances the understanding of Big Data Analytics (BDA) adoption and Smart Supply Chain Management (SmSCM) performance in Malaysian manufacturing by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with three contextual constructs—Technology Readiness (TR), Perceived Risk (PR), and Trust. The PLS-SEM analysis revealed that Effort Expectancy (EE), Facilitating Conditions (FC), and Trust significantly influenced Usage Behavior (UB), while Price Value (PV) and Perceived Risk (PR) were non-significant. This differs from Dwivedi et al. (2022), who found PV to be a strong driver of adoption in broader digital transformation contexts. The divergence may stem from the Malaysian manufacturing sec-tor's prioritization of operational reliability and data security over cost considerations, particularly in BDA initiatives where upfront investment is often mandated.

The finding that Trust exerts a stronger influence on UB than PV challenges traditional UTAUT2 assumptions, which typically position cost–benefit perceptions as central to adoption decisions. In a context where BDA systems handle sensitive operational and customer data, trust in system reliability, vendor integrity, and data governance frameworks becomes pivotal. This aligns with Kshetri (2021), who emphasized that in emerging economies, perceived trustworthiness can outweigh economic incentives in technology adoption decisions.

Technology Readiness emerged as a meaningful mediator, bridging the gap between antecedents and UB. This supports Parasuraman's (2000) original assertion that readiness is not merely a user trait but a strategic lever that organizations can enhance through training, leadership support, and infrastructure investment. The integration of TR into the UTAUT2 framework addresses criticisms regarding the original model's limited focus on the "capability to adopt" dimension, especially in resource-constrained environments.

The results also substantiate the conceptual link between UB and SmSCM performance, confirming that behavioral adoption translates into measurable operational outcomes such as improved visibility, agility, collaboration, and decision quality. This outcome addresses the gap identified by Zhou et al. (2020), who noted that most behavioral adoption studies stop short of linking usage to downstream performance metrics.

Based on these findings, a revised UTAUT2 model for BDA adoption retains key UTAUT2 constructs (EE, PE, FC, PV) but prioritizes Trust and TR, while excluding Hedonic Motivation and Social Influence. It also explicitly connects UB to SmSCM performance, creating a bridge between behavioral theory and performance-based frameworks. This configuration offers stronger explanatory power for emerging market contexts and a foundation for hybrid explanatory–predictive analytics.

B. Practical Recommendations

Firms seeking to maximize SmSCM performance through BDA adoption should prioritise initiatives that build

Trust and enhance Technology Readiness. This involves:

Trust building measures – Establishing robust data governance policies, obtaining internationally recognised security certifications (e.g., ISO/IEC 27001), and maintaining transparent vendor relationships can reduce apprehension over data misuse and system failures.

Technology Readiness training – Investing in targeted skills development, such as analytics literacy programs and cross-functional digital competency workshops, can significantly improve UB. Given the SVM's ability to predict high SmSCM performance with 80.9% F1-score for the High category, enhancing TR could directly improve predictive accuracy and real-world outcomes.

Facilitating Condition enhancement – Aligning IT infrastructure with BDA requirements, ensuring system compatibility, and providing continuous technical support can remove adoption barriers and sustain engagement.

The machine learning results demonstrate that behavioral constructs can be leveraged for predictive performance classification. Firms can deploy similar models internally to identify business units or plants with high potential for performance improvement. This enables targeted interventions, such as prioritizing resource allocation or implementing specific capability-building programs in low-performing areas.

C. Policy Implications

At a policy level, the findings indicate that national strategies for Industry 4.0 should place stronger emphasis on reducing Perceived Risk and improving Technology Readiness. Possible interventions include:

Government subsidies for BDA infrastructure – Financial incentives, tax rebates, or low-interest loans for digital infrastructure investment can lower the perceived financial and operational risk of adoption.

National training frameworks – Public–private partnerships could deliver sector-specific analytics and data governance training, particularly for SMEs, which are most constrained by skill shortages.

Standardization and certification – Implementing national standards for BDA interoperability and security can increase trust in technology systems and vendor solutions.

By aligning industrial policy with the key behavioral determinants identified in this study, policymakers can accelerate adoption and performance outcomes across the manufacturing sector.

CONCLUSION

This study presents a hybrid methodological framework that integrates Partial Least Squares Structural Equation Modelling (PLS-SEM) with supervised machine learning (ML) to predict Smart Supply Chain Management (SmSCM) performance based on Big Data Analytics (BDA) adoption indicators. Grounded in the UTAUT2 framework and extended with constructs such as Technology Readiness, Trust, and Perceived Risk, the research provides both explanatory insights and predictive capabilities within the context of Malaysian manufacturing firms.

The PLS-SEM results validate the influence of key behavioral and organizational factors particularly Effort Expectancy, Facilitating Conditions, and Trust on BDA usage behavior. Furthermore, BDA usage significantly predicts SmSCM performance, reinforcing the strategic importance of analytics adoption in digital supply chains. These findings not only confirm prior theoretical propositions but also offer empirical evidence specific to emerging market contexts.

The application of ML, especially Support Vector Machine (SVM), demonstrates the feasibility of forecasting supply chain performance based on behavioral indicators. The classification model achieved a predictive accuracy of 70.66%, indicating that firm-level adoption characteristics can serve as reliable inputs for data-driven performance assessment. This dual approach bridges the methodological gap between behavioral modelling and out-come prediction, offering a robust decision-support framework for practitioners.

In sum, this study contributes to academic literature by proposing a validated, predictive model for BDA-driven SmSCM transformation. For practitioners, the model provides a structured diagnostic and forecasting tool that can support strategic investments in digital technologies. Future research may further refine this framework by incorporating sector-specific variables, real-time analytics data, or physio-logical measures to enhance predictive precision and contextual relevance.

While the study contributes to both theory and practice, certain limitations must be acknowledged. First, the sample comprised primarily mid- to senior-level managers, potentially introducing positional bias toward strategic perspectives, while operational insights from technical staff were underrepresented. Future research should adopt a multilevel sampling approach to capture both strategic and operational viewpoints.

Second, the cross-sectional design limits the ability to infer causal relationships over time. A longitudinal study tracking firms from adoption through to maturity could reveal how behavioral determinants evolve and interact with performance metrics.

Third, while the binary classification of SmSCM performance via median split ensured balanced classes for ML modelling, it may have oversimplified performance variation. Future work could adopt multi-class or regression-based predictive modelling to capture a more nuanced performance spectrum.

Fourth, predictive modelling relied on behavioral constructs alone. Incorporating IoT-derived operational data—such as real-time inventory turnover, lead time variability, and production yield—could improve prediction accuracy, especially for Low-performance firms, which the current model struggled to classify (F1 = 50.0%).

Finally, while SVM emerged as the best-performing model in this study, further exploration of ensemble learning techniques and explainable AI (XAI) approaches could yield both higher accuracy and greater interpretability, making predictive analytics more actionable for decision-makers.

ACKNOWLEDGMENT

The authors would like to acknowledge the support provided by Universiti Teknikal Malaysia Melaka (UTeM) for the facilities and academic resources that enabled the completion of this research. Special thanks are also extend-ed to the participating Malaysian manufacturing firms for their time and insights during the data collection

REFERENCES

1. Aronoff, S., (1989). Geographic Information Systems: A Management Perspective. Ottawa: WDL Publications.
2. Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2022). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a revised theoretical model. Information Systems Frontiers, 24(1), 1–16. https://doi.org/10.1007/s10796-021-10141-5
3. Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2020). Empirical examination of UTAUT2 in the context of mobile payment adoption. Information Systems Frontiers, 22(1), 293–314. https://doi.org/10.1007/s10796-018-9862-7
4. Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the UK: A multi-perspective framework. Journal of Enterprise Information Management, 26(3), 250–275. https://doi.org/10.1108/17410391311325225
5. Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. Production and Operations Management, 27(10), 1868–1883. https://doi.org/10.1111/poms.12838
6. Chong, A. Y.-L., Ch'ng, E., Liu, M. J., & Li, B. (2017). Predicting consumer product demands via Big Data: The roles of online promotional marketing and online reviews. International Journal of Production Research, 55(17), 5142–5156. https://doi.org/10.1080/00207543.2017.1292063
7. Frederico, G. F., Garza-Reyes, J. A., Anosike, A., & Kumar, V. (2021). Supply Chain 4.0: Concepts, maturity, and research agenda. Supply Chain Management: An International Journal, 26(2), 262–

282. https://doi.org/10.1108/SCM-09-2020-0454

8. Gupta, S., Modgil, S., & Gunasekaran, A. (2020). Big data in lean six sigma: A review and future research directions. International Journal of Production Research, 58(3), 947–969. https://doi.org/10.1080/00207543.2019.1598599
9. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE Publications.
10. Hazen, B. T., Skipper, J. B., Ezell, J. D., & Boone, C. A. (2016). Big data and predictive analytics for supply chain sustainability: A theory-driven research agenda. Computers & Industrial Engineering, 101, 592–598. https://doi.org/10.1016/j.cie.2016.06.030
11. Ivanov, D., Dolgui, A., & Sokolov, B. (2022). Cloud supply chain: Integrating Industry 4.0 and digital platforms in the "Supply Chain-as-a-Service". Transportation Research Part E: Logistics and Transportation Review, 160, 102676. https://doi.org/10.1016/j.tre.2022.102676
12. Kshetri, N. (2021). Blockchain and trust in supply chain management. In Blockchain and supply chain management (pp. 3–23). Springer. https://doi.org/10.1007/978-3-030-73659-4_1
13. Kshetri, N. (2021). Blockchain and trust in supply chain management. In Blockchain and supply chain management (pp. 3–23). Springer. https://doi.org/10.1007/978-3-030-73659-4_1
14. Liao, Y., Deschamps, F., Loures, E. D. F. R., & Ramos, L. F. P. (2017). Past, present and future of Industry 4.0: A systematic literature review and research agenda. International Journal of Production Research, 55(12), 3609–3629. https://doi.org/10.1080/00207543.2017.1308576
15. Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for SMEs. Journal of Manufacturing Systems, 49, 194–214. https://doi.org/10.1016/j.jmsy.2018.10.005
16. Ngai, E. W. T., & Gunasekaran, A. (2020). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014
17. Ooi, K. B., Lee, V. H., Tan, G. W. H., Hew, T. S., & Hew, J. J. (2018). Cloud computing in manufacturing: The next industrial revolution in Malaysia? Expert Systems with Applications, 93, 376–394. https://doi.org/10.1016/j.eswa.2017.10.009
18. Sanders, N. R., & Wagner, S. M. (2021). Big data and supply chain management: A review and research agenda. Journal of Business Logistics, 42(1), 81–105. https://doi.org/10.1111/jbl.12264
19. Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. Journal of Business Logistics, 36(1), 120–132. https://doi.org/10.1111/jbl.12082
20. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189
21. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified Theory of Acceptance and Use of Technology 2: A theoretical model extension. MIS Quarterly, 40(1), 283–301. https://doi.org/10.25300/MISQ/2016/40.1.06
22. Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2020). How "big data" can make big impact: Findings from a systematic review and a longitudinal case study. International Journal of Production Economics, 165, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031
23. Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2022). Big data analytics in logistics and supply chain management: A predictive analytics perspective. Transportation Research Part E: Logistics and Transportation Review, 114, 210–225. https://doi.org/10.1016/j.tre.2016.04.007
24. Wichmann, P., Brintrup, A., Baker, S., Woodall, P., & McFarlane, D. (2020). Extracting supply chain maps from news articles using deep neural networks. International Journal of Production Research, 58(17), 5320–5336. https://doi.org/10.1080/00207543.2019.1671629
25. Zailani, S., Jeyaraman, K., Vengadasan, G., & Premkumar, R. (2012). Sustainable supply chain management in Malaysia: Key drivers and performance outcomes. International Journal of Operations & Production Management, 32(9), 984–1011. https://doi.org/10.1108/01443571211265684
26. Zhou, K., Liu, T., & Zhou, L. (2020). Industry 4.0: Towards future industrial opportunities and challenges. International Journal of Production Research, 58(6), 1922–1940. https://doi.org/10.1080/00207543.2019.1672905