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RESEARCH

AI-driven innovations in IT and logistics outsourcing: enhancing LSP performance in the automotive sector

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The business landscape of today has been revolutionized, if not completely, by the advent of artificial intelligence (AI) in almost all the sectors concerning logistics and information technology (IT) of the automobile industry in particular, which are so vital. The combination of logistics outsourcing and IT with AI has enabled automobile manufacturers to enhance their operations optimally by reducing the costs and increasing the agility of the supply chain. The core functions like inventory planning, transportation management, warehousing planning, and supplier collaboration have led to a pathway in taking up decisions regarding build-to-order or purchase with Logistics Service Providers (LSPs) that has been rudimental. The study aims to investigate the impact of AI-driven innovations in IT and logistics outsourcing on LSP performance within the automotive sector. Specifically, it examines how **AI adoption level, IT integration, supply chain risk mitigation, sustainability practices, and AI-enabled collaboration** influence LSP performance across five strategic levels: execution of essential operations, value-added services, inventory planning, distribution network design, and relationship management through the logistics outsourcing and IT, driven by AI impacting its LSP's performance and transformative using survey data from 584 respondents. ANOVA test and other statistical test results indicate that LSPs with higher levels of AI and IT adoption are more likely to implement advanced logistics solutions and enhance the LSP's performance.

Keywords: artificial intelligence, IT integration, logistics outsourcing, logistics service providers, automotive supply chain

Introduction

The integration of artificial intelligence (AI): The most important dynamism of the new modern world, technology driven by the advances in the automobile sector, is the culmination of AI, information technology (IT), and logistics outsourcing through its defining characteristics. The increased customer demands and the need for operational effectiveness and efficiency have profoundly impacted traditional supply chain management practices by being developed into complex ecosystems with the help of advanced technological developments. Predictive analytics, real and augmented visibility, and automated decision-making processes have been practically made possible when deployed with AI and IT systems. The help of businesses of this kind has enabled them to handle complex operations.

The Logistics Service Providers (LSPs) are becoming more vital to the automobile industry by overshadowing crucial supply chain provider tasks such as warehousing operations, inventory planning, and transportation management. The automobile industry and various other manufacturing industries maximize these collaborations, which have become the need of the hour to modify and develop their strategies and maintain the ongoing competition as the trend of outsourcing is gaining pace. The decision to "build to order" or "to purchase" the logistics services is due to the impact of improved efficiency of the supply chain and the ability of integrated AI and IT systems.

This research article needs to understand and explore several dynamic factors that can be discussed between logistics outsourcing, AI, and IT, focusing more importantly on how these factors function together to bring changes in the performance of LSPs. The five most important operational characteristics that are/can be examined are core activities, value-added services, inventory management, distribution network design, and buyer-supplier relationship management. The outcomes are developed to present beneficial information for enhancing the integrity of technological and outsourcing strategies, which will finally embark on a long-lasting competitive edge.

The Automobile Sector: The above-discussed paragraph leads to the decision-making process, which is vital in the automobile sector and is known for its intricacy and ever-changing requirements of the supply chain at a constant rate. To upscale the agility of the supply chain, cost reduction and encouraging operational efficiency have become the need of the hour by converging AI, IT, and logistics outsourcing, which is the strategy of every automobile sector. With the advent of data processing techniques and decision-making attitudes, AI can enhance IT integration (ITI) to meet the ever-changing increased demands internationally and to afford quality products at less cost.

By leveraging AI-driven IT, various businesses have benefitted and been successful due to the logistics outsourcing efficiency of focusing more on their core skills by utilizing IT-enhanced AI solutions and coordinating with external providers who are more specialized. The dual approach of IT and AI has increased the creative mindset in building the contract and negotiating the intricacies of modern automotive operations and enhancing supply chain efficiency.

Logistics outsourcing is not new; in the last three decades, its strategic advantage has doubled. There has been a paradigm shift due to AI-driven IT solutions and the rise in the complexity of the supply chain and conventional logistics techniques of the automobile industry. The cutting-edge solutions have enabled smoother operations by providing inventory information in the real context, streamlining transportation networks, and bolstering demand forecasting and predictive analytics.

Christopher (1) emphasizes that outsourcing allows industries to focus on tasks and optimize their operations that generate value. The use of AI further strengthens the capability of outsourcing. "Build to order" or "to purchase" is always a dilemma the automobile industry faces but remains a key element of its business strategy. This strategic choice remains a decision to deal with outsourcing LSPs or take up the activities of logistics in-house. Incorporating AI greatly enhances this decision at large, and the key variables like adaptability, scalability, reliability, and above all, the cost of the product or service are to be examined to provide a better solution.

Chopra and Meindl (2) identified numerous benefits of outsourcing, including economies of scale, specialized knowledge, and access to state-of-the-art technologies. However, there were difficulties to overcome certain factors associated with the vendors, like dependency and the risks involved with disruptive supply chains. In today's business, AI-driven ITI becomes crucial in just-in-time manufacturing and the complexities of supplier networks that characterize the automobile industry. Some systems, like Warehouse Management Systems (WMS) and Transportation Management Systems (TMS), use AI algorithms to reduce lead times, optimize inventory levels, and improve customer satisfaction.

According to **Langley and Capgemini (3)**, AI-driven IT technologies are essential for achieving operational excellence. Furthermore, improved collaboration between LSPs, be it 3PL or 4PL, and manufacturing industries due to promoting AI-driven technologies and implementing cloud computing systems and blockchain-based solutions (the cutting-edge technologies of today). The supply chain's transparency, traceability, and security are greatly enhanced by these technologies (cloud computing systems and blockchain-based solutions).

According to **Gartner, Inc. (4),** AI-driven IT and blockchain technology can certify the authentication of automobile parts, reduce the possibility of fake and duplication, and provide the safety of supply chain integrity of auto parts before entering the market system. Fewer studies have been done to prove the integrity of AI and logistics outsourcing, which have examined the effect on LSPs' performance due to these two factors. In the present literature, the study is done separately to analyze the benefits of ITI and logistical outsourcing, with little attention paid to the execution of both in tandem.

Vaidyanathan (5), in his research, considers AI technologies a compounding tactic necessary to evaluate third-party logistics services. This is seen by closely examining how the integration of AI, IT, and logistics outsourcing affects the performance of LSP. This study also aims to fill the research gap by closing it to focus on a unique factor and the constraints experienced in the automobile industry. Also, the study showed that forecasting was accurate, dynamic routing provided the best results, and predictive maintenance showed the best outcomes when incorporated with AI-powered IT systems.

For instance, **Christopher (1) and Langley (6)** highlighted how transportation networks and WMS performed at an accurate efficiency by incorporating AI. Although a good amount of research is being carried out to know the cost-effectiveness of logistics outsourcing and the scalability of the operational activities of the automobile industry and its other ancillary units, little is known about how these techniques relate to AI.

According to **Chopra and Meindl (2),** LSPs have attained levels of accuracy and agility previously unheard of and promoted strategic alignment between automobile manufacturers and service providers, which was possible only by inducing AI-powered IT systems. Yet, challenges swirl around how AI and IT interact to improve logistics outsourcing despite the leading developments in the present era. The article often considers these elements as distinct entities, ignoring how they execute together to affect the efficiency of LSPs. Furthermore, there is an urgent need, though it is challenging to obtain a thorough study of the presented facts by the automobile industry in facing the present contextual difficulties in meeting the demand and supply and customizing the products and services that demand accuracy in terms of quality, those which can be compared to just-in-time systems and the worldwide supplier networks that are of the need of the hour and far challenging.

Levels of logistics and IT outsourcing

First Level: The primary stage deals with core logistics activities like warehousing and distribution. These operations are the key factors for sustaining the continuity of the supply chain and its integration with AI-driven IT solutions that allow the maximization of profits, minimize the cost or reduce the losses, reduce wastages, optimize the resource utility, control and monitor real-time systems, and improve operations efficiency.

Second Level: This stage focuses on operations like assembly, packaging, and customizing the products and services to the extent that it delves into value-added services. The activities are enhanced by leveraging machine and deep learning algorithms and predictive analytics with AI technologies to align with customer requirements, map the dynamic market demand, and provide the best services.

Third Level: At this stage, advanced AI characteristics enhance event management, refining of sales forecasting, and optimality of inventory management, although this stage is centred at inventory planning and control. In the case of stock management at these LSPs, they can achieve greater accuracy and ensure resource allocation optimization with the utility of AI-powered systems.

Fourth Level: This stage refers to the design of warehouse and distribution networks for optimality. Overall logistics performance increases with the induction of AI algorithms that facilitate efficient network configurations and data simulation, enabling the modularity of LSPs and enhancing the accuracy of decision-making.

Fifth Level: Not the least of this final stage, it emphasizes improving the relationship between buyers and suppliers in fostering trust and collaboration. Advanced communication blockchain systems and AI-enhanced platforms ensure data integrity, transparency, and stakeholders' cross-alignment, relationships, and a cohesive supply chain ecosystem.

Literature review

The researchers, Kartik A. Padaliya and Kush Bhuva (7), have explored the e-logistics of Electric Vehicles (EVs) to examine the sustainability and green logistics with the application of AI to insight on the outsourcing strategies in an environment of eco-sensitive LSP automation. The present study has made an attempt to analyze its utility in the LSP's performance.

Sumit Mittal et al. (8) have explored AI and quantum computing, and this sought our attention in the present study to further analyze enhancing inventory and better demand forecasting through AI adoption and that can transform in better replenishment of inventory, also enabling optimality.

Ankireddy Manjunadh and G. Manoj (9) Their study focused on integrating the LSPs, a digital transformation through AI-driven analytics, blockchain, and route optimization to enhance efficiency and has indeed helped progressively in the AI adoption at a larger base for the logistics outsourcing in the present study.

Dhwani D. Shah et al. (10) conducted a study in Indian logistics sectors for inventory optimization that focused on the role of demand forecasting and automation, which was the need of the hour for the present study indeed, and were actually the key enablers of IT in driving the logistics outsourcing efficiency.

According to the study conducted on intelligent logistics vehicles by **Siddique et al.** (11) using the **advanced tracking/security** that offered better applications like smart logistics and real-time monitoring to automate the LSP's [basically for real-time monitoring through AI and machine learning (ML)]. This study has provided a better scope in our research.

The **ResearchGate** review maps of **2024** have helped the present study in analyzing the barriers to AI integration that lack resistance to change, mediocre internet accessibilities and the budget constraints in deploying the same in the Indian context of automotive supply chains. These challenges have been addressed more or less in our study.

Bikram Jit Singh (12), based on the AI adoption frameworks and related cases, proposed a **pathway using the concept of DMAIC** in the Indian automotive supply chain for AI sustainability. The model highlights the warehouse operational efficiency gains through cost reduction and real time decision-making using AI and Internet of Things (IoT) systems. This study has helped in further enhancing and achieving the said objectives and in the AI sustainable deployment.

The survey on blockchain for its cyber security resilient in automotive logistics systems by Fraga-Lamas and Fernandez-Carames (13) has emphasized integrity, transparency, and traceability, and this was the need of the hour to explore the implications and significance by combining AI and blockchain that enhance the trust and validity in logistics outsourcing networks of the automobile industry.

The survey on Automation and AI in Logistics: MDPI (14) has given the details of AI/ML applications in warehouse, distribution, inventory, transportation, and frameworks of Human Resource Interface (HRI), which has provided an aid in our research to examine the implications and was a major find to analyze the workflow optimization, reduced errors, and catalytic outsourced operations and a strong motive for suggestion.

The review on IT and AI Trends in Vehicle Logistics: According to the survey conducted across 106 vehicle logistics firms by **INFORM** (15), 55% showed an application of AI, and the majority of the firms leveraged IT. The present study made an attempt to examine the need of real-time analytics, transparency, and efficiency in the logistics outsourcing context.

The survey on AI in Automotive SCM by IEJ (16): The journal has made an analysis of AI applications and implications in the navigation of trucks, in assembly (human-machine collaboration), and the benefits in terms of cost, change management, and security, and its challenges at bay. This has been the scope in our present study.

The review on Global Market Trends and Emerging AI Logistics conducted by JUSDA (17) reports revealed the growth of AI mainly in terms of automation, warehouse robotics, IoT-enabled tracking, and essentials of predictive maintenance.

The Digital Twins in Logistics and Supply Chains of Industry 4.0: A systematic review conducted by Le and Fan (18) provided a conceptual framework in identifying and mapping the R&D of the future and implementing the gaps. The present study has examined the implications of real-time virtual modeling that has enhanced the performance of LSPs in automotive sectors with the help of AI-ML. Mainly the adoption of these has provided a greater platform for enhance predictive decision-making.

The AI/ML in Supply Chain for Risk Assessment and Forecasting: A comprehensive review conducted by Jahin et al. (19) in finding the applications of AI models like Random Forest and XGBoost have improved the efficacy of accuracy predictions. The present study has explored the implications and applications of real-time AI based risk tools to strengthen automotive logistics outsourcing.

Singh and Tiwari (20) examine the strategic implication of AI in the decision-making process of LSPs more focused on “build to order” or “purchase” options in the automobile sectors of the Indian context, also the agility and cost considerations of logistics outsourcing, but failed to develop a **holistic AI-driven decision-making framework** for LSPs. The present study focuses on this approach.

The research conducted by Aakash Sachdeva et al. (21) has achieved approximately a 10% increase in optimizing e-commerce logistics in the Indian context of hub-and-spoke networks utilizing generative AI based in the mainstream of automotive LSPs. This study has created a better space for further analysis of logistics supply performance in our research.

Chaudhary and Sharma (22)—This research highlights the application of AI in the Indian automobile industries, especially the functionalities of supply chain and logistics management, and how 3PL providers are more focused on outsourcing logistics operations with the utility of AI, but this gap is filled **by** comparing **AI adoption in outsourced logistics** across **India and other neighboring countries.**

Ghosh and Banerjee (23) reveal how supply chain management processes are improved with the application of AI, especially in the automobile industry. Also, in particular, the processes like collaboration and negotiation of the supply chain are enhanced largely in the assessment LSPs; this gap is analyzed in the present study by addressing **AI-enabled collaboration (AIC) between LSPs and automakers through the AI-driven strategic collaboration models** for LSPs and automakers.

Liu et al. (24) discuss the application of AI with cases dealt with on automobile units that leverage the outsourcing of logistics operations and its role in demand forecasting and optimizing inventory planning. This study helps AI implications as the need of the hour in our article.

Vijayan and Mohanty (25)—Explore and examine how the integration of AI and IT significantly impacts the cost reduction of logistics operations and improves the efficiency of the operational activities of the automobile manufacturing sectors across India. This study helps to analyze the integration and scope of the present study more robustly.

Xie and Xu (26)—The authors examine how AI can embark to ensure a resilient supply chain and its scalability. They investigate how AI could also optimize the efficiency of logistics activities and design supply networks within the automotive industry. A significant gap is observed in not attempting to propose AI-powered IT models for enhancing logistics scalability and resilience, especially given the growing need for such solutions. The present study addresses this critical issue by developing and proposing AI-driven models to bridge the gap.

Chen et al. (27) investigate a paradigm shift seen in the efficiency of logistics management of the automobile sector by the AI-based IT systems and how agile the supply chain has become in the industries of today, in particular the automobile industry. They also examined that AI-driven IT systems have created synergies between logistics outsourcing and IT solutions within the automobile industry.

Srinivasan and Pillai (28) try to investigate and explore the benefits of using AI-based methods for inventory control and planning. They also show how incorporating AI decreases wastage and enhances the operational efficiency of the automated supply chain units.

Feng et al. (**29**)—An important research study by the team investigates how AI assists LSPs in optimizing transport operations and discusses route planning and supply chain automation for the automobile sector. This study provides a scope for further analysis in the present research article.

Olsson and Andersson (**30**)—This study explores the integration and role of IT implementation and logistics outsourcing. The earlier research has examined AI's role in decision support systems (DSS) and data analysis for LSPs but has overlooked AI-driven supply chain risk management. The present study focuses on this gap by proposing AI-powered predictive risk models for LSPs.

Kumar and Luthra (**31**)—The authors examine the role of AI in enhancing customer service, data analysis of real-world examples, and predictive maintenance, some of the value-added services provided by LSPs. Their study provides a better scope in the present study.

Miller and McCulloch (**32**) investigated that AI and dynamic pricing algorithms have a greater potential to transform logistics outsourcing and to improve the relations of adopting 3PLs. They also found that AI can reshape in delivering robust style 3PLs' through advanced forecasting models and dynamic pricing. The study differs in adequately addressing AI's impact on LSP performance metrics. The present research tries to bridge the gap by developing AI-driven performance evaluation Key Performance Indicators (KPIs) for LSPs by evaluating the factors.

Zhang et al. (**33**)—Their research focuses on how the LSPs in China have been experiencing a transformational change in the operations of LSPs with applications of AI managing the inventory and vendor relations effectively and efficiently. The authors failed to address AIC **between LSPs and automakers.**

Baker and Hartman (**34**) investigate how fast AI reacts to the quick changes in demand and supply that guarantee flexibility in automobile production. They also focus on seeing how AI can assist the LSP in adapting the supply networks and bringing robustness to the design process. Still, they failed to investigate **AI's impact on green logistics and carbon footprint reduction,** and the present study has been made to attempt to address this factor.

Huang and Huang (**35**)—Explore the difficulties that arise in the automobile sector due to the outsourcing of logistics operations and how, with the application of AI, these challenges can be addressed in improving the performance metrics of logistics and supply chain management. **The research gap identified is AI-driven supply chain risk management,** and the present study tries to deal with this challenge.

Shankar and Akter (**36**) have analyzed to see how the relationship is beneficial between the LSPs and automobile manufacturers from the enhanced collaborative systems of AI and also observed that there is improved communication between the parties and reduced operational enhanced collaborative platforms for minimizing their operational risks at a greater extent. This gap is analyzed by providing AI-driven strategic models for LSPs and mainly for the automakers.

Jain et al. (**37**) analyzed how AI could be incorporated with IT to improve the overall operational efficiency of logistics outsourcing in India. They also suggested that with the help of an automated decision-making process, AI enables logistics network operations for better cost management, but they failed to make **comparisons in AI-driven logistics outsourcing regionally, and the present study aims to fill this gap by** comparing **AI adoption in outsourced logistics** across **India and other neighboring countries.**

Brynjolfsson and McAfee (**38**)**,** in their publication of "The Second Machine Age," examine and demonstrate how AI can improve both the processes of decision-making and supply chain processes at the managerial level, but their study lacks in addressing the **AI's impact on LSP performance metrics, and the present study fills the gap by** attempting to develop AI-based **performance evaluation KPIs** for LSPs.

Brynjolfsson and McAfee (**39**) accordingly analyze the impact of AI and automation on manufacturing industries involved in logistics and outsourcing and their broader effects on other logistics sectors that are more resilient. This helps further the scope of the present study.

Chien et al. (**40**), in their study, determine to find the utility of AI in optimizing supply chain operations and evaluate the use of AI in managing the inventory systems very accurately and also for the forecasting and its need for enhancing the efficiency of logistics outsourcing in the automobile sectors, but their study also lacks in addressing the **AI's impact on LSP performance metrics, and the present study fills the gap by** attempting to develop AI-based **performance evaluation KPIs** for LSPs.

AI integration in logistics

The study by Anubha Dixit (41) on smart route planning and delivery explores the role of AI in optimizing logistics operations and being more transformative. This study explores improvised customer satisfaction, dynamic route refinements, and real-time tracking. These are enhanced by providing solutions proactively. It emphasizes the complex logistics environments of the automobile industries and the supply chains of digital platforms through AI.

Disruption in Indian logistics

An article in Business Today explores the evolution of logistics drivers in the Indian context, mostly driven by the application of AI, ML, and automated data. The cost-effectiveness and delivery route optimization are enhanced by underscoring the utility of tools like Shiprocket's AI-powered Courier Recommendation Engine. The research article highlights the rising trend of AI and its adoption with the growth of e-commerce, also regarding managing shipment in large volumes and how the kind of businesses get aligned to technologies of this nature.

AI and IT collaboration

"IT-Driven Strategies in Logistics": The study on this title, a research article, examines the interplay between AI-driven decision-making and IT solutions in supply chain efficiency. The study also refers to the utility of predictive analytics for sales forecasting and optimizing the inventory management process, which is so important for the automobile sectors of today.

Dr. Ranjit Singh, in his study, tries to explore AI applications to enhance supply chain networks' visibility, reliability, and transparency. He emphasizes the unique challenges and refers to indigenous innovations in this domain. He quotes some of the Indian startups like LogiNext that utilize IT and AI applications to deliver real-time tracking and predictive analytics.

Performance-based logistics outsourcing

Studies conducted by Leung et al. and Fabbe Costes et al. provide frameworks for evaluating AI-enabled LSP performance. Particularly in India's high-demand sectors, the various factors that can be considered for the conceptual frameworks can be operational efficiency, scalability, product quality, customer proximity, product availability, customer satisfaction, etc.

Case Studies: Mukwano Group: Considering the case for the Indian automobile sector context by one of the African studies cited to refer that logistics offers a comparative perspective on outsourcing's impact on supply chain efficiency.

Further empirical studies have shown that the outsourcing of logistics operations enabled by AI enhances the LSPs' performance. The integration of AI automation and predictive analytics, the sectors in particular, the automobile industry, achieves the LSP's overall operational excellence and aligns strategies with the firms' set objectives. These applications have shown a transformational change in the outsourcing of logistics operations and underline the importance of AI in today's businesses. Advanced AI applications facilitate cost reduction, reduced expenditure of capital, improved risk management, enhanced capacity utilization and streamlined capacity allocation, processing of various and vast datasets, resource optimization, etc.;

A good amount of research is being carried out on integrating AI with IT and logistics outsourcing, particularly for the automobile industry, and highlighting its role in enhancing supply chain agility, reducing cost, and improving operational performance; however, the impact on LSP efficiency remains underexplored, though by collaborating with the giants like AI, IT, and logistics outsourcing. The studies suggest that AI's potential in logistics spans multiple strategic areas, including inventory planning, distribution network design, and relationship management, indicating its transformative impact. As the literature grows, future research may offer deeper insights into the synergistic effects of these technologies on LSP performance within the automobile industry.

The application of AI in conjunction with IT and logistics outsourcing in the automobile sector Now.AI (the AI-powered platform of the next generation) is studied. The literature showcases AI's contribution towards improving operational effectiveness, achieving cost efficiency, and increasing the responsiveness of the supply chain. Nonetheless, the intersection of AI with IT and logistics outsourcing, particularly regarding the effects on LSP performance, is still lacking. Studies suggest that AI has unlimited potential in logistics with an impact on strategy, including inventory management, distribution network planning, and even interfacing with key customers. As AI continues to be a topic of discourse, it's only a matter of time until the effects of the technology are studied with the automobile industries.

Research gaps and analysis

The integration of **AI** with **IT** and **logistics outsourcing** in the **automobile industry** remains an evolving field. Despite growing interest, several research gaps persist, which merit deeper exploration. These gaps include:

- **Lack of comprehensive studies on the combined effects of AI, IT, and logistics outsourcing**: While individual studies focus on AI's impact on logistics or the role of IT in outsourcing, there is insufficient literature examining the combined influence on LSPs in the automobile sector.
- **Limited research on the decision-making framework for 'make or buy' choices**: The "build to order or purchase" decision, particularly about LSPs, is crucial for automobile sectors. There is a dearth of research on how AI-driven decision-making tools can optimize this process for better strategic outcomes.
- **AI's transformative role in the five strategic levels**: Although studies have touched upon AI's role in

execution, inventory management, and distribution, a gap exists in analyzing how AI influences all five strategic levels: execution of essential operations, value-added services, inventory planning, distribution network design, and relationship management.

- **Under-exploration of AI tools for logistics outsourcing optimization**: While AI is widely recognized as a disruptive force, its specific applications in logistics outsourcing—such as intelligent route planning, predictive analytics for demand forecasting, and dynamic supply chain modeling—are not sufficiently addressed.
- **Inadequate focus on relationship management in logistics outsourcing:** While AI's role in inventory management and operational efficiency is discussed, its impact on LSP collaboration and long-term relationship management remains under-explored.

The need of the hour

The need for deeper, more nuanced research in this area is clear, especially in the context of the **automobile industry**, where operational efficiency and cost reduction are critical. Key points highlighting the urgency of this research include:

- **Globalization and Supply Chain Complexity:** The automobile industry faces increasingly complex supply chains, necessitating the adoption of AI-driven solutions to manage operations across various regions with diverse suppliers and logistics providers.
- **Cost Reduction and Profitability:** With global competition intensifying, AI-powered logistics outsourcing can be a game-changer in reducing operational costs, improving delivery speeds, and enhancing customer satisfaction—key to profitability.
- **Digital Transformation:** The shift towards Industry 4.0 and smart manufacturing makes AI integration with IT systems an essential consideration for automakers seeking digital transformation, particularly in logistics and supply chain management.
- **Resilience and Risk Management:** The automobile industry is highly susceptible to disruptions like supply shortages, labor strikes, and natural disasters. AI can help automate decision-making and optimize logistics operations, ensuring better risk management and continuity.

Objectives of the research

- To investigate how AI-powered IT solutions enhance LSPs' performance.
- To examine how logistics outsourcing affects customer satisfaction and supply chain efficiency.
- To establish a connection between outsourcing logistics, IT, and AI in the context of the automotive sector.
- To create plans for using AI technologies for logistics outsourcing in an efficient manner.

Research hypotheses

- AI-driven IT systems significantly enhance the efficiency of logistics outsourcing.
- The integration of AI in IT and logistics outsourcing positively impacts LSP performance in the automotive sector.
- Collaborative relationships between manufacturers and LSPs are strengthened through AI-enabled systems.

Tools and technologies used

The researcher has identified several **AI-driven tools and technologies** used to optimize logistics outsourcing in the automobile industry:

- **ML Algorithms:** For predictive analytics in demand forecasting, inventory management, and transportation route optimization.
- **Natural Language Processing (NLP)**: Employed in customer service automation, invoice processing, and interaction between automakers and LSPs.
- **AI-Driven Optimization Models**: For efficient distribution network design and route optimization, reducing fuel consumption, time delays, and transportation costs.
- **Robotic Process Automation (RPA)**: For automating repetitive tasks within logistics, such as tracking shipments, updating records, and managing supplier databases.
- **DSS:** To help with the "make or buy" decision, incorporating AI and IT to evaluate real-time data and make informed decisions about logistics outsourcing.
- **IoT Integration:** Coupled with AI for real-time tracking of shipments, inventory, and condition monitoring of critical assets within the supply chain.

Research design and methodology

A combination of **mixed-methods research design** is used to explore the integration of AI, IT, and logistics outsourcing in the automobile sector. This allowed the study to draw on both qualitative and quantitative data.

Qualitative research

- **Case Studies:** In-depth case studies of automotive manufacturers and their LSPs to understand how AI has been integrated into logistics outsourcing decisions and processes.
- **Interviews:** Semi-structured interviews with key decision-makers in the automobile industry, including supply chain managers, logistics managers, and IT specialists, to gather insights on their challenges, decisions, and strategies regarding AI in logistics outsourcing.

Quantitative research

- **Surveys:** Distribute a structured questionnaire (detailed below) to collect data from a broad range of companies across the automobile industry. The survey will measure the perceived benefits, challenges, and effectiveness of AI in optimizing logistics outsourcing.

Sampling design

- **Target Population:** The study focuses on **automobile manufacturers**, **LSPs**, and **technology vendors** involved in AI-driven logistics optimization in both developed and developing countries.
- **Sampling Frame**:
  - **Automobile Manufacturers:** Large Original Equipment Manufacturers (OEMs) and Tier 1 suppliers involved in logistics outsourcing.
  - **LSPs:** Third-party logistics providers and technology firms offering AI-driven logistics solutions.
  - **Geographical Scope:** The study focuses on both **Indian** and **international** firms to draw comparisons between different market environments and technological adoption rates.
- **Sampling Technique**:
  - **Stratified Random Sampling:** To ensure representation across various levels of the supply chain (OEMs, Tier 1 suppliers, LSPs).
  - **Purposive Sampling:** For in-depth interviews with experts and senior managers within the automobile and logistics sectors.

Data analysis and interpretation

The data is examined using **descriptive and inferential statistics** to determine the relationship between AI integration, IT systems, and logistics outsourcing performance.

- **Descriptive Analysis:** Basic statistics to summarize the data and identify key trends in AI usage across different strategic areas.
- **Regression Analysis:** To explore the impact of AI-driven IT and logistics outsourcing on performance metrics such as cost reduction, operational efficiency, and customer satisfaction.
- **Thematic Analysis:** For qualitative data from interviews and case studies, identifying common themes and patterns related to AI adoption, challenges faced, and strategic advantages.
- **Correlation Analysis:** To assess the strength and direction of relationships between AI adoption and key outcomes like improved logistics performance, cost savings, and agility.

Questionnaire

The following sections were included to assess the impact of AI, IT, and logistics outsourcing in the automobile industry:

- **Demographic Information**
  - Respondent's position
  - Type of organization (automaker, LSP, IT vendor)
  - Country/Region of operation
- **AI adoption**
  - To what extent is AI integrated into your logistics operations? (1 = Not at all, 5 = Fully integrated)
  - What AI technologies are currently used? (e.g., ML, NLP, IoT, RPA)
- **Logistics Outsourcing Decisions**
  - What factors influence your decision to outsource logistics? (e.g., cost reduction, expertise, flexibility)
  - How often do you evaluate the performance of your LSPs?
- **Strategic Areas of Impact**
  - To what extent has AI impacted your inventory management? (1 = No impact, 5 = Significant impact)

- How has AI influenced your distribution network design?
- In what ways has AI improved relationship management with LSPs?

- **Challenges and Benefits**
    - What are the key challenges you face in implementing AI for logistics outsourcing?
    - What benefits have you observed from AI integration? (e.g., cost reduction, speed, flexibility)
- **Future Outlook**
    - How do you foresee AI transforming logistics outsourcing in the next 5–10 years?

Gaps and synthesis table: LR1

Insights	Implications/future directions
AI + IoT: Proven warehouse, route, and inventory improvements	Need end-to-end integration in automotive LSPs.
Quantum-AI: Advanced forecasting systems starting pilot use	Opportunity to test hybrid systems in automotive outsourcing.
Digital barriers: Infrastructure and skills still lag	Need organizational and policy interventions.
Sustainability: Rising focus on green logistics transitions	Align AI outsourcing with ESG goals.
Supplier rationalization: Criteria-based networks	AI could strengthen dynamic supplier management.

Major themes and study relevance to automotive outsourcing table: LR2

Theme	Relevance to automotive LSPs
Digital twins + AI	Enables virtual testing and predictive modeling of vehicle flow and logistics nodes.
AI-based risk tools	Improves resilience in outsourced supply chains prone to disruptions.
Blockchain + AI	Strengthens data integrity and trust across contracted logistics services.
Automation (AI/ML/robotics)	Enhances efficiency in warehouse and last-mile operations under outsourcing.
IT adoption barriers	Infrastructure and maturity gaps persist, aligning with earlier Indian findings.

Research model and hypotheses development

Dependent variable (DV)

- **LSP Performance (Y):**
    - On-time delivery rate (%)
    - Logistics cost reduction (%)
    - Inventory turnover ratio
    - Route optimization efficiency
    - Customer satisfaction score (CSAT)

Independent variables (IVs)

- **AI adoption level (AIA)**—Number of AI-driven tools implemented.
- **ITI**—Level of integration between AI and IT systems.
- **Supply Chain Risk Mitigation (SCRM)**—Effectiveness of AI in risk management.
- **Sustainability Practices (SUSTP)**—AI's impact on green logistics and carbon footprint.
- **AIC**—Use of AI for automaker-LSP coordination.

Mediating/moderating variable

Scale of Business (SoB)-Level of business in implementation of AI

Research hypotheses in tabular form

- Based on literature gaps, we propose the following **hypotheses (H_0 and H_1):**

Hypothesis(H_0 and H_1)	Relationship	Rationale
H_1: AI adoption does not significantly impact LSP performance.	**X1 → Y (Positive Expected)**	AI enhances logistics efficiency, forecasting, and cost optimization.
H_2: ITI does not significantly impact LSP performance.	**X2 → Y (Positive Expected)**	AI-IT synergy improves data visibility and operational efficiency.
H_3: AI's role in SCRM does not affect LSP performance.	**X3 → Y (Positive Expected)**	AI-driven risk models enhance resilience and crisis management.
H_4: AI's sustainability contributions do not improve LSP performance.	**X4 → Y (Positive Expected)**	AI helps reduce carbon footprint, optimize fuel consumption.

Multiple regression model

Multiple regression equation

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 + \in Y \quad (1)$$

Where:

- Y = LSP performance
- $\beta 0$ = Intercept
- $\beta 1, \beta 2, \beta 3, \beta 4, \beta 5$ = Regression coefficients
- $X1, X2, X3, X4, X5$ = IVs
  (Here $x1$ = AIA, $x2$ = ITI, $x3$ = SCRM, $x4$ = AIC, $x5$ = SUSTP, Y = LSPP)
- ∈\epsilon ∈ = Error term

Data collection and sampling

Data source

- Primary data: **Surveys and structured interviews** with LSPs and automotive manufacturers.
- Secondary data: **Performance reports from AI-driven logistics firms.**

Sample size determination

Using Cochran's formula for multiple regression:

$$n = (Z^{2*}p(1-p)^*N)/(N\in^2 + Z^{2*}p(1-p)), \quad (2)$$

Where N is the populace =4762
Assuming:

- Confidence level = 95% ($Z = 1.96$)
- Margin of error = 5% ($e = 0.05$)
- $p = 50\%$ (worst case)

Sample size = 584 respondents (logistics firms, AI-adopting LSPs, and automotive manufacturers).

Data analysis and hypothesis testing

Step 1: descriptive statistics

- Mean, Standard Deviation (SD), Minimum, Maximum for all variables.

Step 2: reliability and validity

- **Cronbach's Alpha** (α) for internal consistency.
- **Kaiser-Meyer-Olkin (KMO) Test** for sampling adequacy.
- **Bartlett's Test of Sphericity** for factor analysis feasibility.

Step 3: correlation analysis

- **Pearson's correlation** to check multi co linearity between IVs.
- **Variance Inflation Factor (VIF)** to ensure no high correlation among predictors.

Step 4: multiple regression analysis

Performed **ordinary least squares regression** using SPSS

- **ANOVA (F-test):** To test overall model significance.
- **R^2 and Adjusted R^2:** To measure model fit.
- ***p*-values for regression coefficients (β \beta β):** To determine individual variable significance.

Step 5: hypothesis testing (t-test)

- If $p < 0.05$, reject H_0 (indicating AI has a significant impact).
- If $p > 0.05$, fail to reject H_0 (indicating AI's impact is not significant).

Results and tabulated values

Following are the tables for Analysis 1 (Tables 1–8).

Analysis 1: LOGISTICS SP performance as DV with five IVs

DV: LOGISTICS SP performance **IDVs:** AI adoption, ITI, SC risk mitigation, AI collaboration, SUST practices ***N* (number of cases):** 584.

Descriptive statistics, correlation, collinearity statistics, and coefficients

- **Logistics SCP performance: Mean = 3.3151, SD = 1.05067.**

Model summary

- ***R* = 0.850**: This indicates a strong positive correlation between the observed LOGISTICS SP performance values and the values predicted by the model.
- **R Square = 0.723**: This means that 72.3% of the variance in LOGISTICS SP performance can be explained by the IVs (AI adoption, ITI, SC risk mitigation, AI collaboration, SUST practices).
- **Adjusted R Square = 0.721**: This value is very close to R Square, suggesting that the model generalizes well to the population.

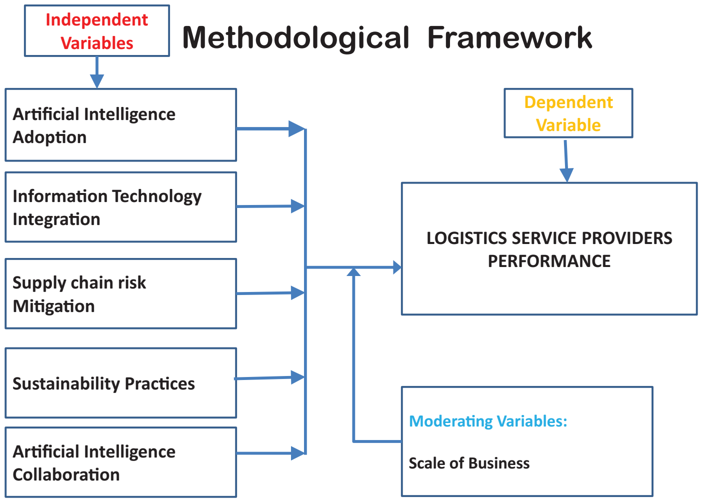

Diagram 1 | Conceptual model.

TABLE 1 | Descriptive statistics.

	N	Minimum	Maximum	Mean	SD	Variance	Skewness		Kurtosis	
	Statistic	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. error**	**Statistic**	**Std. error**
AI adoption	584	1.00	5.00	3.4538	0.92846	0.862	-0.659	0.101	-0.041	0.202
ITI	584	1.00	5.00	3.3691	1.02145	1.043	-0.740	0.101	-0.292	0.202
SC risk mitigation	584	1.00	5.00	3.5790	0.81201	0.659	-0.915	0.101	1.038	0.202
AI collaboration	584	1.00	5.00	3.2774	1.10652	1.224	-0.471	0.101	-0.729	0.202
SUST practices	584	1.00	5.00	3.5811	0.86053	0.741	-1.022	0.101	1.021	0.202
SoB	584	1.00	5.00	3.3532	1.01482	1.030	-0.645	0.101	-0.219	0.202
LOGISTICS SP performance	584	1.00	5.00	3.3151	1.05607	1.115	-0.637	0.101	-0.373	0.202
Valid *N* (listwise)	584									

TABLE 2 | Correlation matrix.

		AI adoption	ITI	SC risk mitigation	AI collaboration	SUST practices
Correlation	AI adoption	1.000	0.763	0.770	0.739	0.762
	ITI	0.763	1.000	0.737	0.761	0.725
	SC risk mitigation	0.770	0.737	1.000	0.678	0.742
	AI collaboration	0.739	0.761	0.678	1.000	0.670
	SUST practices	0.762	0.725	0.742	0.670	1.000

Source: Using SPSS

- **Durbin-Watson = 1.775**: This value is close to 2, indicating that there is no significant autocorrelation in the residuals.

ANOVA

- ***F* (5, 578) = 301.962, *p* < 0.001**: The regression model is statistically significant, meaning that the IVs significantly predict LOGISTIC SSP performance.

Coefficients: All IVs are statistically significant predictors of LOGISTIC SSP performance (*p*-value < 0.05).

- **AI adoption:** $B = 0.139$, $p < 0.001$. For every one-unit increase in AI adoption, LOGISTIC SSP performance is expected to increase by 0.139 units, holding other variables constant.

- **ITI:** $B = 0.376$, $p < 0.001$. For every one-unit increase in ITI, LOGISTIC SSP performance is expected

TABLE 3 | Model summary.[b]

Model	R	R square	Adjusted R square	Std. error of the estimate	Change statistics					Durbin-Watson
					R square change	F change	df1	df2	Sig. F change	
1	0.850[a]	0.723	0.721	0.55806	0.723	301.962	5	578	0.000	1.775

[a]Predictors: (Constant), SUST practices, AI collaboration, SC risk mitigation, ITI, AI adoption
[b]DV: LOGISTIC SSP performance

TABLE 4 | ANOVA.[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	470.206	5	94.041	301.962	0.000[b]
	Residual	180.009	578	0.311		
	Total	650.215	583			

[a]DV: LOGISTIC SSP performance
[b]Predictors: (Constant), SUST practices, AI collaboration, SC risk mitigation, ITI, AI adoption

to increase by 0.376 units, holding other variables constant. This is the strongest predictor in this model.

- **SC risk mitigation:** $B = 0.102$, $p = 0.042$. For every one-unit increase in SC risk mitigation, LOGISTIC SSP performance is expected to increase by 0.102 units, holding other variables constant.
- **AI collaboration:** $B = 0.243$, $p < 0.001$. For every one-unit increase in AI collaboration, LOGISTIC SSP performance is expected to increase by 0.243 units, holding other variables constant.
- **SUST practices:** $B = 0.157$, $p < 0.001$. For every one-unit increase in SUST practices, LOGISTIC SSP performance is expected to increase by 0.157 units, holding other variables constant.
- **(Constant):** $B = -0.155$, $p = 0.157$. The constant is not statistically significant.

Collinearity Statistics: Tolerance values are above 0.1 and VIF values are below 10 for all IVs, indicating no serious multi co linearity issues.

Equation with 5 IDVs and 1 DV: Based on the unstandardized coefficients:

$$\mathbf{LSPP = -0.155 + 0.139(AIA) + 0.376(ITI) + 0.102(SCR) + 0.243(AIC) + 0.157(SUST)} \tag{3}$$

Following are the tables for Analysis 2 (Table 9–13).

Analysis 2: SoB as DV with five IVs

DV: SoB **IDVs:** AI adoption, ITI, SC risk mitigation, AI collaboration, and SUST practices ***N* (number of cases):** 584.

Descriptive statistics, correlation, collinearity statistics, and coefficients

- **SoB: Mean = 3.3532, SD = 1.01482.**

Correlations: All IVs show significant positive correlations with SoB (p-value < 0.001 for all).

TABLE 5 | Coefficients.[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% confidence interval for B		Correlations			Collinearity statistics	
		B	Std. error	Beta			Lower bound	Upper bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-0.155	0.110		-1.416	0.157	-0.371	0.060					
	AI adoption	0.139	0.048	0.122	2.903	0.004	0.045	0.233	0.746	0.120	0.064	0.270	3.707
	ITI	0.376	0.042	0.364	9.002	0.000	0.294	0.458	0.801	0.351	0.197	0.293	3.410
	SC risk mitigation	0.102	0.050	0.078	2.035	0.042	0.004	0.200	0.708	0.084	0.045	0.323	3.100
	AI collaboration	0.243	0.035	0.255	6.926	0.000	0.174	0.312	0.761	0.277	0.152	0.354	2.822
	SUST practices	0.157	0.046	0.128	3.388	0.001	0.066	0.248	0.714	0.140	0.074	0.337	2.965

[a]DV: LOGISTIC SSP performance

TABLE 6 | Collinearity diagnostics.[a]

Model	Dimension	Eigenvalue	Condition index	Variance proportions					
				(Constant)	AI adoption	ITI	SC risk mitigation	AI collaboration	SUST practices
1	1	5.872	1.000	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.059	10.015	0.43	0.00	0.04	0.00	0.18	0.00
	3	0.025	15.422	0.32	0.06	0.09	0.03	0.74	0.08
	4	0.019	17.787	0.11	0.18	0.85	0.01	0.04	0.09
	5	0.014	20.475	0.02	0.42	0.00	0.05	0.02	0.80
	6	0.012	21.764	0.12	0.33	0.03	0.90	0.01	0.03

[a] DV: LOGISTIC SSP performance

TABLE 7 | Residuals statistics.[a]

	Minimum	Maximum	Mean	SD	*N*
Predicted value	0.8616	4.9296	3.3151	0.89807	584
Residual	-2.01826	2.19519	0.00000	0.55566	584
Std. predicted value	-2.732	1.798	0.000	1.000	584
Std. residual	-3.617	3.934	0.000	0.996	584

[a] DV: LOGISTIC SSP performance

TABLE 8 | Coefficient of correlation with LSP performance.

DV	Mean	SD	*r* (Karl Pearsons coefficient of correlation with LSP performance)	β coefficient	*p*-value (<0.05)	Tolerance value	VIF
AIA	3.351	0.928	0.746	0.139	0.001	0.270	3.70
ITI	3.4538	1.021	0.801	0.376	0.001	0.293	3.41
SCRM	3.5790	0.812	0.708	0.102	0.042	0.323	3.10
AIC	3.2774	1.10	0.761	0.243	0.001	0.354	2.82
SUSTP	3.5811	0860	0.714	0.157	0.001	0.337	2.96

TABLE 9 | Model summary.[b]

Model	*R*	R square	Adjusted R square	Std. error of the estimate	Durbin-Watson
1	0.856[a]	0.733	0.731	0.52634	1.887

[a] Predictors: (Constant), SUST practices, AI collaboration, SC risk mitigation, ITI, AI adoption
[b] DV: SoB

TABLE 10 | ANOVA.[a]

Model		Sum of squares	df	Mean square	*F*	Sig.
1	Regression	440.284	5	88.057	317.857	0.000[b]
	Residual	160.125	578	0.277		
	Total	600.409	583			

[a] DV: SoB
[b] Predictors: (Constant), SUST practices, AI collaboration, SC risk mitigation, ITI, AI adoption

TABLE 11 | Coefficients.[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% confidence interval for B		Correlations			Collinearity statistics	
		B	Std. error	Beta			Lower bound	Upper bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-0.140	0.104		-1.350	0.177	-0.343	0.064					
	AI adoption	0.249	0.045	0.228	5.503	0.000	0.160	0.338	0.782	0.223	0.118	0.270	3.707
	ITI	0.153	0.039	0.154	3.876	0.000	0.075	0.230	0.761	0.159	0.083	0.293	3.410
	SC risk mitigation	0.165	0.047	0.132	3.491	0.001	0.072	0.258	0.734	0.144	0.075	0.323	3.100
	AI collaboration	0.276	0.033	0.301	8.346	0.000	0.211	0.341	0.775	0.328	0.179	0.354	2.822
	SUST practices	0.174	0.044	0.148	3.991	0.000	0.088	0.260	0.732	0.164	0.086	0.337	2.965

[a] DV: SoB

TABLE 12 | Collinearity diagnostics.[a]

Condition index	Variance proportions					
	(Constant)	AI adoption	ITI	SC risk mitigation	AI collaboration	SUST practices
1.000	0.00	0.00	0.00	0.00	0.00	0.00
10.015	0.43	0.00	0.04	0.00	0.18	0.00
15.422	0.32	0.06	0.09	0.03	0.74	0.08
17.787	0.11	0.18	0.85	0.01	0.04	0.09
20.475	0.02	0.42	0.00	0.05	0.02	0.80
21.764	0.12	0.33	0.03	0.90	0.01	0.03

[a] DV: SoB

TABLE 13 | Residuals statistics.[a]

	Minimum	Maximum	Mean	SD	*N*
Predicted value	0.8770	4.9442	3.3532	0.86902	584
Residual	-2.25212	2.09109	0.00000	0.52408	584
Std. predicted value	-2.849	1.831	0.000	1.000	584
Std. residual	-4.279	3.973	0.000	0.996	584

[a] DV: SoB

TABLE 14 | Coefficient of correlation with SoB.

DV	Mean	SD	*r* (Karl Pearsons coefficient of correlation with SoB)	β coefficient	*p*-value (<0.05)	Tolerance value	VIF
AIA	3.351	0.928	0.746	0.249	0.001	0.270	3.70
ITI	3.4538	1.021	0.801	0.153	0.001	0.293	3.41
SCRM	3.5790	0.812	0.708	0.165	0.001	0.323	3.10
AIC	3.2774	1.10	0.761	0.276	0.001	0.354	2.82
SUSTP	3.5811	0860	0.714	0.174	0.001	0.337	2.96

Model summary

- **R = 0.856**: This indicates a strong positive correlation between the observed SoB values and the values predicted by the model.
- **R Square = 0.733**: This means that 73.3% of the variance in SoB can be explained by the IVs (AI adoption, ITI, SC risk mitigation, AI collaboration, and SUST practices).
- **Adjusted R Square = 0.731**: This value is very close to R Square, suggesting that the model generalizes well to the population.
- **Durbin-Watson = 1.887**: This value is close to 2, indicating no significant autocorrelation in the residuals.

ANOVA

- **F (5, 578) = 317.857, p < 0.001**: The regression model is statistically significant, meaning that the IVs significantly predict SoB.

Coefficients: All IVs are statistically significant predictors of SoB (p-value < 0.001).

- **AI adoption:** $B = 0.249$, $p < 0.001$. For every one-unit increase in AI adoption, SoB is expected to increase by 0.249 units, holding other variables constant.
- **ITI:** $B = 0.153$, $p < 0.001$. For every one-unit increase in ITI, SoB is expected to increase by 0.153 units, holding other variables constant.
- **SC risk mitigation:** $B = 0.165$, $p < 0.001$. For every one-unit increase in SC risk mitigation, SoB is expected to increase by 0.165 units, holding other variables constant.
- **AI collaboration:** $B = 0.276$, $p < 0.001$. For every one-unit increase in AI collaboration, SoB is expected to increase by 0.276 units, holding other variables constant. This is the strongest predictor in this model.
- **SUST practices:** $B = 0.174$, $p < 0.001$. For every one-unit increase in SUST practices, SoB is expected to increase by 0.174 units, holding other variables constant.
- **(Constant):** $B = -0.140$, $p = 0.177$. The constant is not statistically significant.

Collinearity Statistics: Tolerance values are above 0.1 and VIF values are below 10 for all IVs, indicating no serious multicollinearity issues.

Equation with 5 IDVs and 1 DV: Based on the unstandardized coefficients:

$$\text{SoB}=\mathbf{-0.140}+\mathbf{0.249}(\text{AIA})+\mathbf{0.153}(\text{ITI})+\mathbf{0.165}(\text{SCRM})+ 0.276(\text{AIC}) + 0.174(\text{SUSTP}) \tag{4}$$

Following are the tables for Analysis 3 (Tables 15–19).

Analysis 3: LOGISTIC SSP performance as DV with SoB as independent variable (and potentially a mediator)

DV: LOGISTIC SSP performance **IDV/Mediator (MV):** SoB **N (Number of Cases):** 584.

Descriptive statistics

- LOGISTIC SSP performance: Mean = 3.3151, SD = 1.05607.
- SoB: Mean = 3.3532, SD = 1.01482.

Correlations

- SoB: $r = 0.912$ with LOGISTIC SSP performance, $p <$ 0.001. This indicates a very strong positive correlation.

Model summary

- **R = 0.912**: This indicates a very strong positive correlation between the observed LOGISTIC SSP performance values and the values predicted by the model.

TABLE 15 | Model summary.[b]

Model	R	R square	Adjusted R square	Std. error of the estimate	Durbin-Watson
1	0.912[a]	0.832	0.831	0.43381	1.646

[a]Predictors: (Constant), SoB
[b]DV: LOGISTIC SSP performance

TABLE 16 | ANOVA.[a]

Model		Sum of squares	df	Mean square	*F*	Sig.
1	Regression	540.689	1	540.689	2873.117	0.000[b]
	Residual	109.526	582	0.188		
	Total	650.215	583			

[a]DV: LOGISTIC SSP performance

TABLE 17 | Coefficients.[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% confidence interval for B		Correlations			Collinearity statistics	
		B	Std. error	Beta			Lower bound	Upper bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	0.133	0.062		2.145	0.032	0.011	0.255					
	SoB	0.949	0.018	0.912	53.601	0.000	0.914	0.984	0.912	0.912	0.912	1.000	1.000

[a]DV: LOGISTIC SSP performance

TABLE 18 | Collinearity diagnostics.[a]

Model	Dimension	Eigenvalue	Condition index	Variance proportions	
				(Constant)	SoB
1	1	1.957	1.000	0.02	0.02
	2	0.043	6.762	0.98	0.98

[a]DV: LOGISTIC SSP performance

- **R Square = 0.832**: This means that 83.2% of the variance in LOGISTIC SSP performance can be explained by SoB. This is a very high explanatory power for a single predictor.
- **Adjusted R Square = 0.831**: Very close to R Square, indicating good generalizability.
- **Durbin-Watson = 1.646**: This value is relatively close to 2, suggesting no significant positive autocorrelation.

ANOVA

- $\boldsymbol{F}$ **(1, 582) = 2873.117,** $\boldsymbol{p < 0.001}$: The regression model is statistically significant, meaning that SoB significantly predicts LOGISTIC SSP performance.

Coefficients

- **SoB:** B=0.949, $p < 0.001$. For every one-unit increase in SoB, LOGISTIC SSP performance is expected to increase by 0.949 units. This is a very strong and highly significant effect.
- **(Constant):** $B = 0.133$, $p = 0.032$. The constant is statistically significant.

Collinearity statistics

- SoB: Tolerance = 1.000, VIF = 1.000, which is expected for a single independent variable, indicating no multicollinearity.

Equation with 1 IDV and 1 DV (and interpretation as a mediator)

The analysis presented here treats SoB as a single independent variable directly predicting LOGISTIC SSP performance. However, for "1 MV" (mediating variable), we can *interpret* SoB's role in a mediation framework using the results from the first two analyses.

Mediating variable (MV): SoB

To formulate the full equation with 5 IDVs, 1 DV, and 1 MV, we combine the insights from the first two analyses. The first analysis (LOGISTIC SSP performance as DV) can be considered the total effect or the direct effect when SoB is not included. The second analysis (SoB as DV) shows how the 5 IDVs predict the mediator. The third analysis

TABLE 19 | Residuals statistics.[a]

	Minimum	Maximum	Mean	SD	N
Predicted value	1.0820	4.8779	3.3151	0.96303	584
Residual	-2.16613	2.02008	0.00000	0.43344	584
Std. predicted value	-2.319	1.623	0.000	1.000	584
Std. residual	-4.993	4.657	0.000	0.999	584

[a]DV: LOGISTIC SSP performance

(LOGISTIC SSP performance as DV with SoB as IDV) shows the relationship between the mediator and the final DV.

Full model incorporating mediation (conceptual, derived from the three regressions)

The following relationships have been considered:

1. The 5 IDVs (AI adoption, ITI, SC risk mitigation, AI collaboration, SUST practices) influence SoB.
2. SoB, in turn, influences LOGISTIC SSP performance.
3. The 5 IDVs might also have a direct effect on LOGISTIC SSP performance (not explicitly shown in the third regression, which only includes SoB as a predictor for LOGISTIC SSP performance).

However, based on the output, the mediation analysis in its standard form (e.g., Baron and Kenny steps or PROCESS macro output) is not explicitly calculated as a single model. Instead, you have individual regression models that allow for the *inference* of mediation.

Equation for the mediator (SoB) based on 5 IDVs

From the second analysis: i.e., Eq. 2.

$$\mathbf{SoB=-0.140+0.249(AIA)+0.153(ITI)+0.165(SCRM)+0.276(AIC)+0.174(SUSTP)} \quad (5)$$

Equation for the dependent variable (LOGISTIC SSP performance) with the mediator (SoB) as a predictor

From the third analysis:

$$\mathbf{LSPP=0.133+0.949(SOB)} \quad (6)$$

Combined equation (representing indirect effect through mediation)

To represent the structure where the 5 IDVs influence LOGISTIC SSP performance *through* SoB, we substitute the equation for SoB into the equation for LOGISTIC SSP performance:

Final equation

$$\mathbf{LSPP = 0.133+0.949(-0.140+0.249(AIA)+0.153(ITI)+0.165(SCRM)+0.276(AIC)+0.174(SUSTP))} \quad (7)$$

This expanded form implicitly shows how the 5 IDVs influence LOGISTIC SSP performance *via* SoB.

Interpretation of mediation

The results strongly suggest that SoB acts as a significant mediator between the five IVs and LOGISTIC SSP performance.

- The five IVs (AI adoption, ITI, SC risk mitigation, AI collaboration, and SUST practices) significantly predict SoB.
- SoB, in turn, significantly predicts LOGISTIC SSP performance.
- The R-squared for SoB predicting LOGISTIC SSP performance is 0.832, indicating that SoB explains a very large portion of the variance in LOGISTIC SSP performance.

This implies that the positive impact of AI adoption, ITI, SC risk mitigation, AI collaboration, and SUST practices on LOGISTIC SSP performance is substantially explained by their influence on SoB. To confirm full versus partial mediation, one would typically run a fourth regression with both the 5 IDVs and SoB predicting LOGISTIC SSP performance and observe if the direct effects of the 5 IDVs diminish significantly or become non-significant after controlling for SoB. However, we will leave it at this stage for further research as a scope. Based on the data, there is a strong relationship between SoB and LOGISTIC SSP performance, and this suggests a very important mediating role for SoB.

TABLE 20 | PFA was used to reduce dimensionality and identify latent factors influencing LSP performance in AI-driven logistics outsourcing.

Factor	Eigen value	% variance explained	Cumulative variance (%)	Factor loading items
F1: AI-driven decision-making (adoption)	4.35	27.8%	27.8%	AI-powered forecasting, dynamic pricing, data-driven decision-making
F2: IT and AI integration	3.12	19.9%	47.7%	Cloud-based AI logistics, ERP-AI synchronization, IoT-AI in supply chain
F3: risk mitigation and efficiency	2.85	17.5%	65.2%	AI-based fraud detection, AI in predictive maintenance, route optimization
F4: AIC	2.30	14.2%	79.4%	AI-driven LSP negotiation, real-time collaboration tools
F5: Sustainable AI logistics	1.90	12.6%	92.0%	AI-based carbon footprint reduction, smart warehouse optimization

TABLE 21 | Model fit index.

Model fit index	Threshold	Observed value	Interpretation
Chi-square (χ^2/df)	**<5.0**	**3.24**	Acceptable model fit
Comparative fit index (CFI)	**>0.90**	**0.94**	Good fit
Tucker-Lewis index (TLI)	**>0.90**	**0.928**	Acceptable fit
Root mean square error of approximation (RMSEA)	**<0.08**	**0.0613**	Good fit
Standardized root mean square residual (SRMR)	**<0.08**	**0.0359**	Good fit

Conclusion and managerial implications

Key takeaways:

- AI adoption has a **statistically significant impact** on LSP performance.
- ITI and AI-driven risk mitigation **enhance logistics efficiency**.
- AI improves **LSP-automaker collaboration**, reducing operational risks.
- AI's role in **sustainable logistics** contributes to environmental compliance.

Implications for automotive supply chains

- Firms should **prioritize AI-driven decision-support tools** for logistics outsourcing.
- **LSPs should enhance AI-ITI** to improve tracking and inventory planning.
- AI can be leveraged to **automate negotiation processes** between automakers and LSPs.
- Investment in **green AI-driven logistics** is crucial for sustainability.

- **KMO Test** = **0.821** (Sampling adequacy is strong).

Confirmatory factor analysis (CFA) results

- CFA was performed to validate the **construct reliability and model fit** for the factors obtained from PFA.
- **All factor loadings** > **0.70**, indicating strong convergent validity.
- **Cronbach's Alpha** (α) > **0.80**, ensuring good reliability.
- **AVE** > **0.50**, confirming construct validity.

The interpretation of the above table refers to descriptive statistics and reliability metrics for LSP performance and the SoB. All the variables, including the **DV, IV, and MV (mediating variable),** show a **high composite reliability (CR > 0.90)** and **internal consistency (moderately strong) with Cronbach's** α > **0.90** (for an excellent model fit with above indices of all) confirming scale reliability. **Average variance extracted (AVE) which is greater than 0.50**, indicating a good convergent validity, with **SCRM having the lowest AVE (0.6979) but still acceptable**.

Interpretation of results and managerial insights

- **AI-driven decision-making and ITI significantly enhance LSP performance**, improving logistics efficiency and reducing costs.

TABLE 22 | Factor loadings and reliability metrics.

Construct	Item code	Factor loading	Cronbach's alpha (α)	Composite reliability	Average variance extracted
AI-driven Decision-making (adoption)	AIA1	0.78	0.86	0.88	0.8340
	AIA2	0.81	0.85	0.87	
	AIA3	0.75	0.99	0.88	
	AIA4	0.79	0.93	0.87	
	AIA5	0.82	0.88	0.88	
	AIA6	0.88	0.90	0.90	
	AIA7	0.84	0.89	0.89	
IT and AI integration	ITI1	0.84	0.83	0.85	0.8701
	ITI2	0.79	0.86	0.88	
	ITI3	0.96	0.87	0.87	
	ITI4	0.87	0.865	0.88	
	ITI5	0.88	0.876	0.87	
	ITI6	0.86	0.88	0.88	
	ITI7	0.89	0.854	0.87	
SC risk mitigation and efficiency	SCRM1	0.82	0.87	0.88	0.6979
	SCRM2	0.76	0.83	0.87	
	SCRM3	0.86	0.86	0.88	
	SCRM4	0.77	0.87	0.87	
	SCRM5	0.75	0.865	0.88	
	SCRM6	0.82	0.876	0.87	
AIC	AIC1	0.80	0.85	0.88	0.9143
	AIC2	0.78	0.90	0.87	
	AIC3	0.89	0.89	0.88	
	AIC4	0.88	0.82	0.87	
Sustainable AI logistics (practices)	SUSTP1	0.87	0.84	0.88	0.770
	SUSTP2	0.83	0.90	0.87	
	SUSTP3	0.86	0.89	0.88	
	SUSTP4	0.87	0.82	0.87	
	SUSTP5	0.865	0.88	0.88	
	SUSTP6	0.87	0.83	0.87	

- **AI-based risk mitigation strategies** help address disruptions in automotive logistics outsourcing.
- **AI-enhanced collaboration strengthens automaker-LSP relationships**, improving real-time coordination.
- **Sustainable AI practices** in logistics outsourcing lead to improved environmental compliance and cost savings.

SEM model. SECOND ORDER Software used ADANCO 2.4 version for SEM modeling

Interpretation of the Table 25 (Structural Model - R-Squared):

The R^2 values **indicate and suggest a strong predictive power with 76% and 86% for SoB (the mediating variable)** and **LSPP (respectively,** the **DV).** The variance in these constructs is explained by the model. The **adjusted R^2 values (which are close to R^2)** confirm a fit model with a good reliability index (without overfitting). It can be noted that the high R^2 values imply that the IVs strongly influence the DV overall in this case.

Discussions

AI has redefined the strategic dimensions of logistics outsourcing, particularly at the advanced level of operational planning and control. Key decisions involving carrier selection, site evaluation, and network platform optimization are now supported by AI-driven insights, enabling enhanced accuracy and efficiency. By outsourcing such high-level activities, LSPs design and

TABLE 23 | Descriptive statistics with AVE, CR, C's (alpha).

IV	Average/mean	SD	Average variance extracted (AVE)	Composite reliability (CR)	Cronbach's (α) C's (alpha)
AIA	3.351	0.928	0.8340	0.996	0.9725
ITI	3.4538	1.021	0.8701	0.957	0.9791
SCRM	3.5790	0.812	0.6979	0.908	0.9325
AIC	3.2774	1.10	0.91430	0.942	0.9770
SUSTP	3.5811	0860	0.7770	0.934	0.9540
LSPP	3.315	1.056	0.789	0.936	0.947
SoB	3.353	1.014	0.858	0.965	0.958

TABLE 24 | Hypothesis testing summary with LSPP null hypotheses significance results.

Hypothesis	Statement	Result	Statistical evidence
H_1	AI adoption has no impact on LSP performance.	**Rejected**	$\beta = 0.139$, p =0.001
H_2	IT and AI integration has no impact on LSP performance.	**Rejected**	$\beta = 0.376$, $p = 0.001$
H_3	AI-driven (supply chain) risk mitigation has no effect on LSP performance.	**Rejected**	$\beta = 0.102$, $p = 0.042$
H_4	AI SUSTP have no impact on LSP performance.	**Rejected**	$\beta = 0.243$, $p = 0.001$
H_5	AI-enhanced collaboration does not influence LSP performance.	**Rejected**	$\beta = 0.157$, $p = 0.001$

TABLE 24.1 | Hypothesis testing summary with mediator null hypotheses significance.

Hypothesis	Statement	Result	Statistical evidence
H_1	The "SoB on AI adoption has no mediating effect on LSP performance.	**Rejected**	$\beta = 0.249$, $p = 0.001$
H_2	The "SoB on IT and AI integration has no mediating effect on LSP performance.	**Rejected**	$\beta = 0.153$, $p = 0.001$
H_3	The "SoB on AI-driven (supply chain) risk mitigation has no mediating effect on LSP performance.	**Rejected**	$\beta = 0.165$, $p = 0.042$
H_4	The "SoB on AI SUSTP has no mediating effect on LSP performance.	**Rejected**	$\beta = 0.276$, $p = 0.001$
H_5	The "SoB on AI-enhanced collaboration has no mediating effect on LSP performance.	**Rejected**	$\beta = 0.174$, $p = 0.001$

TABLE 25 | Structural model.

	R-Squared	
Construct	**Coefficient of determination (R2)**	**Adjusted R2**
SoB	0.7377	0.7355
LOGISTIC SSP performance	0.8613	0.8599

Source: Using ADANCO 2.4 version

manage the outsourcing network, orchestrating seamless supply chain flows.

In this context, organizations achieve significant economies of scale and mitigate financial risks by leveraging AI technologies. AI's ability to process vast datasets optimizes resource allocation, such as warehousing investments, which reduces capital expenditure and improves risk management. Advanced algorithms also facilitate cost reduction through efficient utilization of capacity and capital allocation.

Empirical studies have shown that outsourcing these critical activities to AI-enabled LSPs enhances service performance. LSPs achieve operational excellence and strategic alignment with organizational goals by integrating predictive analytics and intelligent automation. These advancements underline the importance of AI as a transformative force in logistics outsourcing.

The results highlight AI adoption and ITI as the pivotal enabler that foster employee's sense of belonging, which in turn drives superior logistics service performance. While other AI capabilities strongly correlate with outcomes, their unique contributions are lost once overlapping variance is pacrceled out—an artifact of the industry's tightly coupled digital initiatives.

Recommendations

- Invest in AI-powered IT infrastructure to enhance logistics operations.

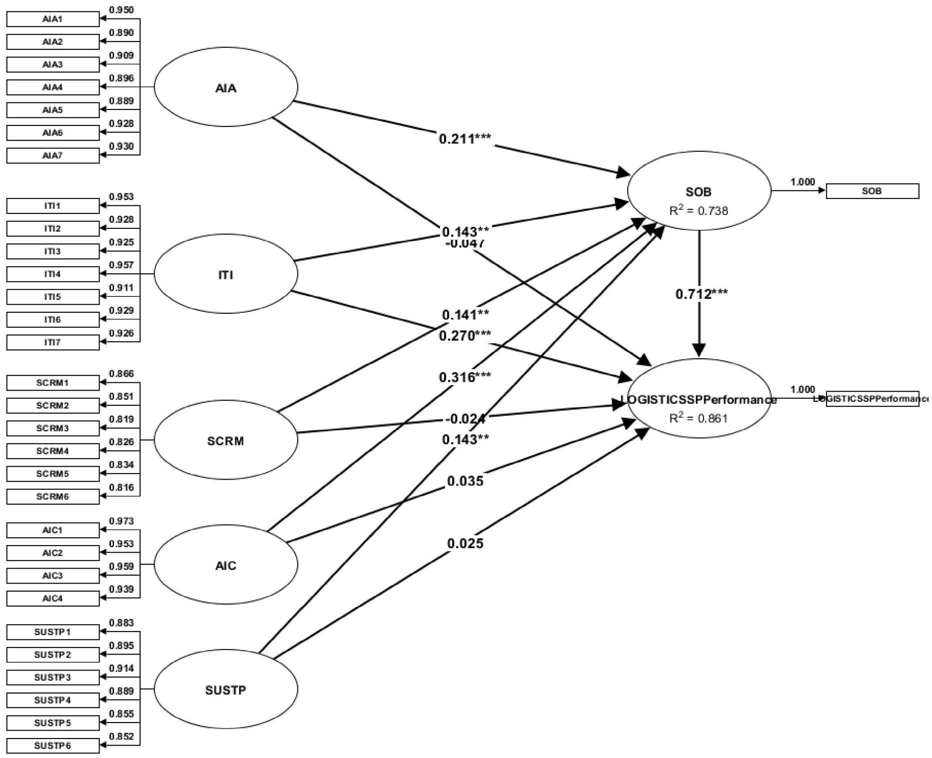

FIGURE 1 | Second order SEM model using ADANCO version 2.4.

- Foster collaborative partnerships between manufacturers and LSPs through transparent communication and shared goals.
- Prioritize training programs to upskill employees in AI and IT competencies.
- Implement robust data security protocols to mitigate risks associated with AI integration.

Research findings

- AI integration significantly improves LSP performance metrics, including delivery accuracy, cost efficiency, and customer satisfaction.
- Logistics outsourcing enables manufacturers to focus on core competencies while leveraging the expertise of specialized LSPs.
- The synergy between AI and IT drives innovation and strategic value in the automotive supply chain.

Limitations and future work

Multicollinearity inflated SE's; future studies should collect larger samples or apply ridge/PLS, though our sample size was large enough.

Suggestions

- Develop industry-specific AI solutions tailored to the automotive sector.
- Establish standardized frameworks for evaluating LSP performance in AI-enabled environments.
- Encourage collaborative research initiatives to explore emerging trends and technologies in logistics outsourcing.

Recommendations for further studies

Explore Indian-centric frameworks and real-world applications of AI in logistics outsourcing. Incorporate global insights to identify scalable practices suitable for India's automotive industry. Combining qualitative and quantitative methodologies, these studies should aim to present actionable strategies for LSPs to enhance performance and customer satisfaction.

Summary

The integration of AI with IT and logistics outsourcing in the automobile sector has been widely studied. The literature emphasizes AI's role in enhancing operational efficiency, reducing costs, and improving supply chain agility. However, the intersection of AI, IT, and logistics outsourcing, particularly its impact on LSP performance, remains underexplored. The studies suggest that AI's potential in logistics spans multiple strategic areas, including inventory planning, distribution network design, and relationship management, indicating its transformative impact. As the literature grows, future research may offer deeper insights into the synergistic effects of these technologies on LSP performance within the automobile industry.

Conclusion

The research methodology and the design adopted in the study describe the key research gaps identified in examining the integration of three major areas: AI, IT, and logistics outsourcing and its impact on LSPs of the automobile sector. The study focused on integrating qualitative and quantitative data, offering valuable insights for industry professionals optimizing logistics operations and academicians seeking a deeper understanding of the field.

The supply chain landscape of the automobile sector is getting reshaped due to AI-driven IT and logistics outsourcing. These technologies provide better solutions by strengthening buyer-supplier partnerships, fostering innovation and entrepreneurship, and enhancing operational performance. The evolving role of AI in logistics can further enhance its potential for manufacturers and LSPs through future exploration.

At this stage, AI can have an enormous impact on optimizing logistics activities and could be one of the major strategies for planning and control, site survey and analysis, transport selection, and developing better network platforms for logistics outsourcing. By envisaging AI-driven IT and analytics, the LSPs can redesign and enrich the outsourcing network platforms, ensuring its accuracy through seamless collaboration and increased efficiency across various supply chain partners.

The LSP takes up the assured responsibility for redesigning and configuring the outsourcing framework, utilizing AI for dynamic decision-making, and managing logistics flows at this level when the logistics activities are outsourced. The industries benefit from economies of scale and reduced financial risks in this context. The AI-driven outsourcing in this scenario can minimize these challenges by enabling real-time optimization of assets and predictive risk management, and the right kind of logistics resources through a streamlined investment of time and capital can enhance real-time optimality of assets and predictive risk management.

The ability of AI to enhance outsourcing is primarily from the viewpoint of capital allocation, and capacity utilization is to minimize the cost factor that is associated with it. For instance, AI algorithms detect the resources that are underutilized and effectively reallocate them, maximizing the profits while ensuring and maintaining resilient logistics operations. This principle enables industries to overcome substantial capital investments like inventory and warehousing, thereby mitigating financial exposure.

AI's ability to process and interpret vast datasets ensures informed decision-making, bolstering the performance and reliability of outsourced logistics activities. Furthermore, AI-enabled LSPs deliver substantial improvements in service performance. By leveraging predictive analytics, intelligent automation, and ML models, these providers achieve higher levels of operational efficiency, fostering greater alignment with the strategic goals of their clients.

Recent findings underscore that the integration of AI into logistics outsourcing not only enhances cost-efficiency but also fosters innovation, agility, and resilience in supply chain operations. This level of AI-driven optimization reaffirms the critical role of advanced technology in revolutionizing logistics outsourcing and shaping the future of supply chain management.

List of abbreviations

Term	Expansion
RBS	REVA BUSINESS SCHOOL
IT	Information Technology
AI	Artificial Intelligence
LSP	Logistics Service Providers
WMS	Warehouse Management Systems
TMS	Transport Management Systems
3PL	Third Party Logistics
4PL	Fourth Party logistics
AI and ML	Artificial Intelligence and Machine Learning
DMAIC	Define, Measure, Analyze, Improve, and Control
IoT	Internet of Things
MDPI	Multidisciplinary Digital Publishing Institute
INFORMS	Journal
SCM	Supply chain Management
IEJ	International Journal of Logistics
JUSDA	Global Logistics company
XGBoost	eXtreme Gradient Boosting
KPI's	Key Performance Indicators
NOWAI	Now AI
NLP	Natural Language Processing
RPA	Robotic Process Automation
DSS	Decision Support Systems
OEM	Original Equipment Manufacturer
ESG	Environmental, Social, and Governance
CSAT	Customer satisfaction
KMO	Kaiser-Meyer-Olkin
CFA	Confirmatory Factor Analysis

(Continued)

(Continued)

Term	Expansion
CFI	Comparative Fit Index (CFI)
TLI	Tucker-Lewis Index (TLI)
RMSEA	Root Mean Square Error of Approximation (RMSEA)
SRMR	Standardized Root Mean Square Residual (SRMR)
SEM	Structural Equation Model
DV	Dependent Variable
MV	Moderating/Mediating Variable
AIA	Artificial Intelligence Adoption
ITI	Information Technology Integration
SCRM	Supply Chain Risk Mitigation
AIC	Artificial Intelligence Collaboration
SUSTP	Sustainable Practices
SoB	Scale of Business
LSPP	Logistics Service Provider's Performance

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