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The Growing Role of AI in Logistics: Trends in Advanced Analytics and E-Business Integration

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ABSTRACT

This study uses a quantitative research strategy to examine the influence of artificial intelligence (AI) techniques and advanced analytics on logistics management. Using a correlational technique, data were gathered from 280 participants from diverse firms that use AI technology in their logistical operations. The study's objectives are to investigate the impact of advanced analytics on operational efficiency, to investigate the link between AI deployment and cost reduction, and to determine how organizational culture influences the relationship between AI adoption and logistics performance results. Participants completed a structured questionnaire utilizing a standardized Likert scale, allowing for an in-depth assessment of their perspectives and experiences with AI technology. The data was analysed using SPSS software, which allowed for the detection of significant connections between important factors influencing logistical operations. The results demonstrate significant links between organizational factors and cutting-edge technology, emphasizing how advanced analytics improves operational efficiency and how AI adoption may result in lower shipping costs. Furthermore, the research underlines the need of an innovation-driven company culture in leveraging the advantages of AI in logistics. The findings show that firms that develop a supportive culture are better positioned to realize performance benefits via AI deployment. This study provides useful insights into the interaction of AI, analytics, and organizational dynamics, emphasizing the need of strategic technology integration in enhancing logistics management results.

Introduction

Artificial intelligence technologies are being utilized to enhance business processes, improve operational performance, and create recommendations for users. They also analyze product demand, identify fraud cases, and improve quality management using digital metrology methods. The rapid growth of results is attributed to the development and use of such systems, which contribute to the growth of interest in AI from both science and practice. However, it is challenging to predict the rate of AI penetration into people's lives and company activities. Overall, AI is gaining importance in both science and practice.

AI, a suite of technologies including machine learning, neural networks, and natural language processing, is rapidly transforming the way logistics support organizations manage supply chains, distribution networks, and transport systems(Szozda, 2017). This integration is critical as logistics is an integral part of international trade and economic development. Traditional manual procedures have led to inefficiencies, human error, and higher costs. However, AI technologies can automate key processes, enhance real-time decision-making, and predict demand fluctuations, optimizing resources. With competition pressures and digital and globalization changes, AI's role in logistics support has become a prime focus for companies. AI is primarily affecting supply chain management by generating large volumes of data, identifying patterns, making inferences on inventory levels, demand forecasting, and shipment tracking. This enables logistics managers to make better decisions, resulting in reduced lead times and stockouts, and better product delivery to customers(Tien et al., 2019).AI, a suite of technologies including machine learning, neural networks, and natural language processing, is rapidly transforming the way logistics support organizations manage supply chains, distribution networks, and transport systems(Akkartal, 2023). This integration is critical as logistics is an integral part of international trade and economic development. Traditional manual procedures have led to inefficiencies, human error, and higher costs. However, AI technologies can automate key processes, enhance real-time decision-making, and predict demand fluctuations, optimizing resources. With competition pressures and digital and globalization changes, AI's role in logistics support has become a prime focus for companies. AI is primarily affecting supply chain management by generating large volumes of data, identifying patterns, making inferences on inventory levels, demand forecasting, and shipment tracking. This enables logistics managers to make better decisions, resulting in reduced lead times and stockouts, and better product delivery to customers.

The rise of digital platforms and marketplaces has transformed commerce, creating e-business ecosystems with interconnected entities(Bahari, 2024). These ecosystems, facilitated by the internet and advanced technologies, are crucial for businesses to thrive in the digital era. They are dynamic and adaptive, constantly evolving in response to technological advancements, market forces, and consumer behaviours. Digital platforms and marketplaces serve as the focal point for economic activities and interactions, providing a virtual space for businesses to showcase their offerings and consumers to discover, purchase, and engage with products and services. Technological innovation, such as artificial intelligence, block chain, and the Internet of Things, continually reshapes the landscape of e-business ecosystems. Research on e-business ecosystems is crucial for understanding scholarly understanding, managerial decision-making, and policy interventions in the digital economy. Previous studies have explored dimensions like platform governance models, network effects, ecosystem sustainability, and value creation mechanisms. However, gaps exist in understanding the underlying mechanisms driving ecosystem dynamics, emerging technologies, and implications for business strategy and public policy(Artioli, 2018).The growth of e-commerce in India is significantly impacting the market, with startups increasingly adopting this mode(Pandey et al., 2024).Online marketplaces have transformed sustainability, offering growth opportunities but also presenting challenges like labor protection and shipping waste(Zarra et al., 2019).

"E-business" refers to the administration and operation of a company via electronic channels, especially the internet(Castillo & Taherdoost, 2023)(Brzozowska & Bubel, 2015). Nevertheless, there are several settings in which the term "e-business" is used. E-business, on the one hand, is defined as technology that enhances internal and external communications, especially for businesses that don't conduct all of their operations online(Sharma & Taherdoost, 2022). Conversely, e-business is a paradigm in which businesses primarily conduct their operations online with little to no in-person connection(Taherdoost & Hosseinkhani, 2013). Beyoncé-Davies and Jones claim that (Beynon-Davies et al., 2016) Two interrelated developments that impact global markets are the growing importance of information and the growing reliance on electronic networks. This indicates that the way firms manufacture, distribute, and utilize their goods is made simpler by technical advancements brought about by increased access to information and communication technology.

Some of the most popular e-business and e-commerce models are listed below:

- **Business-to-Business (B2B):** Exchange of services and products between businesses.
- **Business-to-Consumer (B2C):** Selling services and products to consumers by a business.
- **Consumer-to-Business (C2B):** A consumer provides services and products for a business.
- **Peer-to-Peer (P2P):** Interaction of two individuals without the intermediation of other parties.
- **Government-to-Business (G2B):** Government agencies provide services and products for a business.
- **Government-to-Citizen (G2C):** Interaction between governments and citizens.

Artificial intelligence (AI) is a promising paradigm for addressing supply chain management challenges. By leveraging vast datasets, AI algorithms provide unprecedented insights into supply chain dynamics, enabling optimization in areas such as demand forecasting, inventory management, transportation planning, and risk mitigation. AI's ability to learn and adapt over time enables intelligent systems to respond to changing conditions and optimize performance in real-time. Machine learning algorithms can identify complex relationships within data, facilitating the prediction of future events like demand fluctuations or supply chain disruptions(Siva et al., 2021). AI can also be instrumental in prescriptive analytics, recommending optimal courses of action based on real-time data and historical trends. For example, AI can analyze traffic patterns, weather forecasts, and driver availability to generate dynamic transportation routes that minimize delivery times and fuel consumption. AI can also optimize warehouse operations and picking processes by analyzing historical data on product movement and customer behaviour. AI can also play a transformative role in transportation planning and execution, generating dynamic transportation routes that optimize delivery times and minimize costs.

Artificial intelligence (AI) devices are revolutionizing (Saddique et al., 2024)biotech manufacturing by improving efficiency, creativity, and accuracy(Mehta et al., 2024). They streamline processes from raw material procurement to quality control and supply chain management. Biotech companies are leveraging data analytics and predictive modeling automation to enhance every cycle step, enhancing overall productivity. Predictive maintenance in biotechnology production is crucial due to AI and real-time sensor data. Machines can predict breakdowns, prompting proactive repairs, avoiding costly downtimes. This technology can enhance efficiency, sustainability, and creativity in biotechnology manufacturing through data science, machine learning, and the Internet of Things(Nwagwu et al., 2023).

Objectives

1. To examine the impact of advanced analytics on operational efficiency in logistics operations.
2. To explore the relationship between AI implementation and cost reduction in logistics management.
3. To investigate the moderating effect of organizational culture on the relationship between AI adoption and performance outcomes in logistics.

Advanced analytics: Companies have used analytics for decades, but are increasingly focusing on developing AI capabilities. Many AI systems, however, rely on statistics and other sorts of analytics. Companies may gain a "running start" on AI by improving their analytical capabilities. This article explains how to shift from analytics to AI. The article discusses three periods of analytical attention, with AI being depicted as the fourth. The sorts of AI approaches that rely on analytics and those that do not are outlined. This section discusses AI applications that rely on analytical skills. The article provides a quick overview of analyzing analytical skills related to AI and developing an organizational plan and strategy(Davenport, 2018).(Wang et al., 2020) This article focuses on the online supply chain finance, particularly credit risk, in commercial banks. It uses literature induction to review supply chain financial credit risk indicators, supplementing with online specific indicators. The authors construct an index system for assessing credit risk in the automobile manufacturing industry. The nonlinear LS-SVM model is used for empirical analysis and comparison with logistic regression results. The index system effectively evaluates credit risk, with higher classification accuracy than logistic regression and strong generalization ability. It provides a reasonable and scientific analysis tool for assessing SME credit risk. The article suggests that commercial banks should actively engage in online supply chain finance, comprehensive risk management, and deepen cooperation with e-Business platforms and logistics platforms.

Operational efficiency: (Alsheyadi, 2022)investigated the relationship between e-business practices and performance, focusing on the complementary effects of adopting different types of EB practices on business and operational performance. Data from 108 Omani manufacturing firms was used to examine the model, which was conceptualized as a second-order factor. The study found that the superior effects of the complementarities among various EB practices on business performance were indirect through operational performance, despite variations in firm size and age effects. The study's findings suggest that EB practices can indirectly impact business performance.(Zhu et al., 2020)decomposed an e-business process into technical, relational, and business components using a process component lens. It uses resource orchestration theory to identify two managerial actions: resources structuring and capabilities leveraging in e-business process components. The research reveals two insights: portfolio effects promote platform architecture flexibility and partner engagement in developing e-business operations capabilities (EBOCs) in major e-business processes. The transformation effect of EBOCs in different processes leads to competitive performance. The notion of portfolio and transformation mechanisms offers theoretical and practical implications for developing successful digital supply chain platforms.

AI Implementation: (Malapane, 2019)investigated the influence of Artificial Intelligence (AI) and Internet of Things (IoT) on the transformation of the E-Business Sector in South Africa. AI and IoT are transforming industries globally by generating vast amounts of data. In South Africa, new value can be created through the enabling of transactions. The study aims to investigate and quantify the impact of AI and IoT on the transformation process in the E-Business sector, rather than reproducing experiments.(Rukadikar et al., 2023) investigated the use of Artificial Intelligence (AI) in talent acquisition, comparing traditional methods with AI-adopted processes. It reviews literature on AI's role in talent acquisition and uses a focus group discussion with recruiters from Indian IT companies. The study aims to provide insights on an effective model for using AI in recruiting talent and how AI enhances hiring procedures. The primary data was collected through focus group discussions, and the author discusses how AI can boost the effectiveness of hiring procedures. The study contributes to the body of knowledge by examining various areas of talent acquisition where AI techniques can be successfully applied.

Cost reduction:(Mkansi, 2022) E-business benefits both large and small businesses, but the cost of successful online trading poses a challenge for micro-enterprises. employed a technology-organisation-environment theoretical lens to explore strategies used by e-retail microbusinesses to advance their e-business adoption. The findings reveal the actual cost of adoption, strategies used to lower the cost barrier, and how the pursuit of the cost barrier lowers some adoption barriers outside cost factors. The study also highlights the intrinsic idiosyncratic nature of small firms' ecosystems and the potential for government resources and services to reduce costs associated with e-business adoption.

(Govindan et al., 2018) discussed and evaluated a range of ways to enhance big data analytics and applications for supply chain management and logistics, including by investigating technology-driven tracking tactics, the relationship between data-driven supply chains and financial performance, implementation challenges, and supply chain capability maturity with big data. This editorial note provides a summary of the talks on the characteristics of big data, successful implementation strategies, and assessment and implementation techniques.

(et al., 2018) addressed the gap between supply chain management and data science, two fields that cross. Forecasts, inquiries, and reports are examples of how the data may be evaluated for inventory management, forecasting, and prediction. The projections could not be correct due to the pricing, weather patterns, economic volatility, and intricate nature of company. As a consequence, supply chain analytics have expanded. Big Data applications may be connected for supply chain management in a variety of domains, including marketing, transportation, warehousing, procurement, and smart logistics. The kind of data that is maintained and analysed likewise becomes more complicated as supply chain networks are bigger, more intricate, and driven by expectations for higher service standards. By creating a linear regression model using sales data, the current study seeks to provide an overview of the adoption of data analytics capabilities as part of a "next generation" design. The study also examines the ways in which supply chain data may be stored, processed, managed, interpreted, and visualized using big data approaches.

(Coimbatore, 2021) examined the conventional marketing has changed to digital marketing in response to the internet's and technology's increasing impact on consumer behaviour and corporate tactics. It explores many types of digital marketing, such as social media and search engine marketing, emphasizing how they affect customer choices and the growth of online businesses. By contrasting digital and conventional marketing, it highlights the special benefits and difficulties presented by digital platforms. Finally, by highlighting the importance of digital marketing as a tool for global reach and market penetration, the research clarifies the critical function that digital marketing plays in modern corporate environments.

(Gopal et al., 2024) explored the impact of big data analytics on retail supply chains, focusing on the selection of the best big data practices based on retail supply chain performance. The study uses TODIM (Interactive Multi-Criteria Decision Making) to select the best big data analytics tools from nine practices, including data science, neural networks, enterprise resource planning, cloud computing, machine learning, data mining, RFID, Block chain, IoT, and Business intelligence. The study reveals that most retail firms face a dilemma between customer loyalty and cost when implementing big data practices. The study analyses the dominance of big data practices at the retail supply chain level, helping emerging firms evaluate the best big data practices based on supply chain performance measures.

(Bradlow et al., 2017) investigated the possibilities of big data in retail by concentrating on five important data dimensions: consumers, items, time, location, and channel. The study emphasizes the significance of new data sources, statistical techniques, domain expertise, and theoretical ideas for enhancing data quality and applicability. It also underlines the importance of theory in formulating systematic retailing questions and simplifying analysis. The study also covers the importance of Bayesian analytical approaches, predictive analytics using large data, and field trials in retailing. It also tackles any ethical and privacy concerns that may come from the usage of big data in retail.(Jeble et al., 2016) Big data is a fast expanding subject of study and research, fueled by the rapid rise of the internet and digital gadgets. It includes organized, semi-structured, and unstructured real-time data from diverse sources. Predictive analytics is a way for extracting insight from enormous amounts of data. Companies like Google and Amazon have recognized the value of big data and analytics in achieving a competitive edge. However, large data management and analysis pose issues such as data quantity, quality, dependability, and completeness. This study analyses the literature on big data and predictive analytics, outlining essential principles before concluding with conclusions and future research goals.

Despite the increasing use of AI and advanced analytics in logistics and e-business, some research gaps remain that need additional investigation. While earlier research has shown the importance of analytics in improving organizational skills, there is still a lack of knowledge about how firms may successfully migrate from conventional analytics to AI-driven techniques. The research focuses mostly on the statistical underpinnings of AI applications, but the particular methods for businesses to develop these advanced skills are underexplored. Furthermore, although research has shown that e-business practices improve operations, the intricate interaction between different e-business models and their influence on AI adoption in logistics has received little attention. Furthermore, there is a significant lack of empirical research investigating the practical consequences of AI and IoT integration in the South African e-business setting, despite their transformational potential. The current literature sometimes overlooks the distinct problems and possibilities that local markets bring, notably in terms of credit risk assessment and supply chain financing. This gap also applies to the study of big data techniques in retail supply chains, where research tends to concentrate on theoretical frameworks rather than practical insights customized to varied business situations. Finally, although the rise of digital marketing has been recognized, the convergence of digital marketing techniques with AI applications in logistics need more targeted research to understand the larger implications for consumer behaviour and corporate success. Addressing these gaps might help to progress both academic debate and practical implementations in the logistics and e-business sectors.

The research examines the influence of advanced analytics and AI integration on logistics performance, emphasizing operational efficiency, cost savings, and the significance of corporate culture. It forecasts that sophisticated analytics will enhance efficiency via data-driven decision-making and process optimization, whilst AI will lower costs via automation, resource optimization, and enhanced inventory management. The research examines whether an innovation-oriented organizational culture enhances the correlation between AI adoption and logistics performance outcomes, possibly magnifying its beneficial impacts on efficiency, flexibility, and customer satisfaction.

Hypothesis:

H1: Advanced analytics positively impacts operational efficiency in logistics operations.

H2: AI implementation leads to a reduction in costs associated with logistics management.

H3: Organizational culture moderates the relationship between AI adoption and performance outcomes in logistics, such that a more innovation-oriented culture strengthens this relationship.

Methodology

The study employs a quantitative research, with a correlational strategy, to explore the impact of artificial intelligence(AI) techniques on logistics management. To collect data from the organizations utilizing AI technologies in logistics operations, with a sample size of of 280 divided into two categories i.e. male (153) female (128). The participants were selected through a simple random sampling method. Data were gathered using a structured questionnaire, each participant provide responses using a five Likert scale, ranging from 1(Strongly disagree) to 5(Strongly agree), which facilitated a standardized means of evaluating perceptions and experiences with AI technologies. The data analysis was conducted utilizing SPSS Software, which allowed for the execution of correlation and moderation tests to identify significant relationships between AI techniques and logistics management outcome.

Research frame work

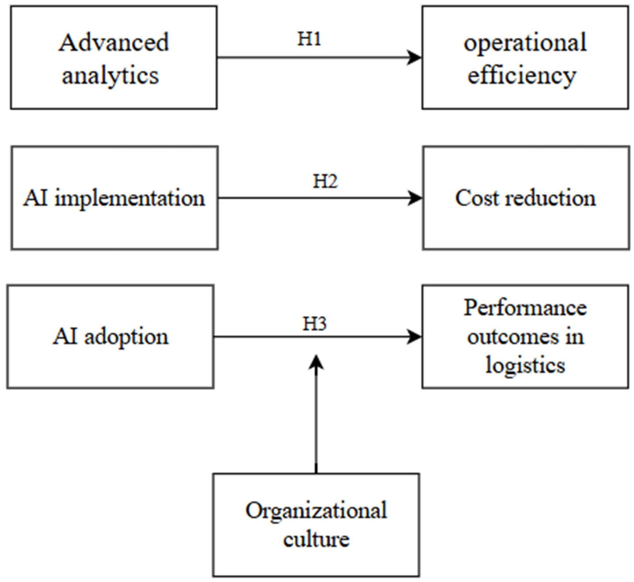

Figure 1 Conceptual frame work

Results

Table 1 Demographic variables

Gender	Frequency	Percent
Male	153	54.6
Female	127	45.4
Total	280	100.0
Age		
Below 29 years	109	38.9
30–44 years	76	27.1
45–59 years	51	18.2
60 years and above	44	15.7
Total	280	100.0
Job Role		
Operational Staff	52	18.6
Middle Management	95	33.9
Senior Management	102	36.4
Executive/C-Suite	31	11.1
Total	280	100.0
Experience		
0–5 years	95	33.9
6–10 years	21	7.5

11–20 years	22	7.9
21 years and above	142	50.7
Total	280	100.0
Education		
High School Diploma	117	41.8
Bachelor's Degree	34	12.1
Master's Degree	53	18.9
Doctorate	76	27.1
Total	280	100.0

Gender

There are 280 participants, with a slight male majority. The total has 153 male (54.6%) and 127 female (45.4%) participants. This distribution allows gender-based analysis due to its gender balance.

Age

In the sample, younger people are over-represented. Youth under 29 make up the majority of participants (109, 38.9%). This is followed by 76 individuals (27.1%) aged 30–44 and 51 (18.2%) aged 45–59. The smallest group is 44 people over 60 (15.7%). This spread lets us study age-based logistics AI adoption patterns.

Job Role

The logistics job role variable shows diversity across levels. Senior Management is the most represented with 102 (36.4%), followed by Middle Management with 95 (33.9%). Executive/C-Suite, the smallest category, with 31 individuals (11.1%), while Operational Staff has 52 (18.6%). This distribution helps analyse AI developments across organisational hierarchies.

Experience:

Experience levels range widely, with a concentration at both extremes. Over 21-year veterans make up the biggest group, 142 (50.7%). There are 95 (33.9%) people with 0–5 years of experience, 21 (7.5%) with 6–10 years, and 22 (7.9%) with 11–20 years. This range lets us examine how experience affects AI and e-business integration views.

Education Level:

The biggest group (117 participants, 41.8%) had a high school diploma. Doctorates make up 27.1% (76 participants), followed by Master's Degrees (53, 18.9%) and Bachelor's Degrees (34, 12.1%). This disparity in education permits examination of how education levels may impact logistics AI and advanced analytics perspectives.

Table 2 Correlations, Means and Standard Deviations

	Age	Gender	Job Role	Year of experience	Educational Level	Advanced analytics	Operational efficiency	AI implementation	Cost reduction	Ai-Adoption	Organisational Culture	Performance outcomes in logistics	Mean	STD deviation
Age	1.00												2.11	1.09
Gender	-0.07	1.00											1.45	0.50
Job Role	.442**	0.10	1.00										2.40	0.91
Year of experience	.527**	-.124*	.501**	1.00									2.75	1.37
Educational Level	.435**	-.147*	.520**	.713**	1.00								2.31	1.26
Advanced analytics	0.11	0.01	.151*	.231**	.236**	1.00							3.71	0.72
Operational efficiency	0.00	0.03	0.09	.130*	0.07	.641**	1.00						3.80	0.74
AI implementation	0.03	0.06	.159**	.139*	0.10	.636**	.562**	1.00					3.61	0.66
Cost reduction	0.05	0.07	.127*	0.11	0.10	.592**	.574**	.733**	1.00				3.61	0.60
Ai-Adoption	0.06	-0.01	.177**	.157**	.147*	.627**	.646**	.659**	.723**	1.00			3.73	0.67
Organisational Culture	0.01	0.02	0.09	0.04	0.07	.635**	.591**	.586**	.587**	.709**	1.00		3.88	0.61
Performance outcomes in logistics	-0.01	-0.02	0.08	0.07	0.06	.555**	.532**	.568**	.581**	.685**	.731**	1.00	3.78	0.63

1. Age

The variable The mean age of respondents is 2.11 and the standard deviation is 1.09, showing a considerable range. Age is strongly connected with Job Role ($r = 0.442$, $p < .01$) and Years of Experience ($r = 0.527$, $p < .01$), indicating older persons tend to occupy higher positions and have more logistical experience.

2. Gender A balanced distribution is seen with a mean of 1.45 and a standard deviation of 0.50. The dataset shows a modest negative association between Years of Experience ($r = -0.124$, $p < .05$) and

Educational Level (r = -0.147, p <.05), suggesting the possibility of gender-specific differences in experience and education.

3. Job Role

Job Role reveals responder position variety with a mean of 2.40 and standard deviation of 0.91. A significant correlation exists between job position, age, experience, and education level (r = 0.442, p <.01). Individuals in higher jobs tend to be older, more experienced, and have higher education levels.

4. Years of Experience

Years of Experience mean 2.75 with standard deviation 1.37. Experience is substantially connected with education level (r = 0.713, p <.01), suggesting that experienced persons tend to have higher education levels. Experienced professionals are more likely to use modern technologies in logistics, as shown by positive associations with modern Analytics (r = 0.231, p <.01) and AI Adoption (r = 0.157,).

5. Education

Education has a mean of 2.31 and an SD of 1.26. It is positively correlated with Years of Experience (r = 0.713, p <.01) and Job Role (r = 0.520, p <.01). Higher education levels are associated with a positive connection with Advanced Analytics (r = 0.236, p <.01), suggesting a greater possibility of using analytics in logistics.

6. Advanced Analytics

The mean Advanced Analytics score is 3.71 with a standard deviation of 0.72. This measure exhibits substantial positive relationships with Operational Efficiency (r = 0.641, p <.01), E-business Integration (r = 0.656, p <.01), and AI Implementation (r = 0.636, p <. Advanced analytics improves logistics efficiency, integration, and AI use, according to these correlations.

7. Operations Efficiency

Due to its mean of 3.80 and standard deviation of 0.74, Operational Efficiency is reasonably efficient in the sample. Significant correlations exist between Advanced Analytics (r = 0.641, p <.01) and AI Adoption (r = 0.646, p <.01), highlighting their importance in driving operational gains.

8. AI Implementation

AI implementation has a 3.61 mean and 0.66 SD. It has substantial positive associations with Customer Satisfaction (r = 0.782, p <.01), Cost Reduction (r = 0.733, p <.01), and Organisational Culture (r = 0.586, p <.01 This shows how AI may save expenses and improve customer satisfaction in adaptable organisations.

9. Cost Reduction

The Cost Reduction mean is 3.61 and the standard deviation is 0.60. Positive correlations exist between AI Implementation ($r = 0.733$, $p < .01$) and AI Adoption ($r = 0.723$, $p < .01$), highlighting the role of AI in logistics cost efficiency.

10. AI Adoption

AI adoption has a 3.73 mean and 0.67 SD. Strong correlations exist with Cost Reduction ($r = 0.723$, $p < .01$), Organisational Culture ($r = 0.709$, $p < .01$), and Logistics Performance Outcomes ($r = 0.685$, $p < .01$). These connections show that AI adoption saves money, improves performance, and fits supportive organisations.

11. Organisational Culture

Organisational Culture has a 3.88 mean and 0.61 SD. A culture that embraces innovation positively correlates with AI adoption ($r = 0.709$, $p < .01$) and Logistics Performance Outcomes ($r = 0.731$, $p < .01$), enhancing both outcomes.

12. Logistics Performance Results

Logistics Performance Outcomes have a mean of 3.78 and a standard deviation of 0.63, indicating strong performance. Research indicates that Organisational Culture, AI Adoption, and Advanced Analytics strongly affect logistics performance results ($r = 0.731$, $p < .01$).

Table 3 Hypothesis Outcomes

Relationship	Estimate	Sig. p	Results
Advanced analytics---> Operational efficiency	0.658	***	Accepted
AI implementation---> Cost reduction	0.669	***	Accepted
Moderating Test			
AI adoption---> Performance outcomes in logistics	0.343,	***	Accepted
Organizational culture ---> Performance outcomes in logistics	0.401	***	
Interaction ---> Performance outcomes in logistics	0.086	***	

The First Hypothesis: Operations Efficiency and Advanced Analytical Capabilities

It has been shown that the concept that advanced analytics has a favourable influence on operational efficiency in logistics operations is validated. According to estimates, the impact size of the association between advanced analytics and operational efficiency is 0.658, which indicates that it is powerful. The statistical significance level, shown by the symbol ***, lends credence to the fact that this particular result is statistically significant, hence resulting in the acceptance of this hypothesis. The conclusion that can be drawn from this is that the use of advanced analytics in logistics significantly improves operational efficiency.

The Hypothesis: How Artificial Intelligence Can Help Reduce Costs

The hypothesis that the installation of AI results in a decrease in costs associated with logistics management is accepted, with an estimated impact size of 0.669. The statistical significance of this association ($p < 0.001$) provides confirmation that the use of artificial intelligence in logistics has a substantial role in efficiently decreasing operational expenses. This discovery lends credence to the idea that artificial intelligence technologies, by means of automation and optimisation, play a significant part in the process of improving the cost efficiency of logistics businesses.

The influence of organisational culture on the relationship between artificial intelligence adoption and performance outcomes is the fourth hypothesis.

With a moderation effect size of 0.343 and a significance level of $p < 0.001$, it must be acknowledged that the moderating influence of organisational culture on the link between the adoption of artificial intelligence and performance outcomes in the logistics industry has been validated. Furthermore, it is worth noting that according to the findings, there exists a positive correlation between organisational culture and performance results, with an impact size of 0.401 (p < 0.00-1). The interaction effect between the adoption of artificial intelligence and organisational culture on performance outcomes reveals a reduced but still significant effect size of 0.086. This suggests that organisational culture magnifies the favourable impact that AI adoption has on performance outcomes. This provides evidence in support of the notion that a culture that is focused on innovation enhances the positive influence that the use of AI has on the performance of logistics.

Discussion:

The findings of the research show that advanced analytics significantly improves operational efficiency in logistics operations (H1). The research now in publication highlights how data-driven decision-making improves logistical procedures by streamlining demand forecasts, inventory control, and route planning. The high positive correlation implies that logistics firms may enhance the overall flow of products, optimise processes, and eliminate bottlenecks as they use sophisticated analytics, eventually leading to efficiency benefits.

The findings further support the hypothesis that the use of AI in logistics management lowers expenses (H3). Automation and predictive maintenance are two examples of AI-driven technologies that have shown a reduction in labour and operating costs via improved predictive capabilities, improved asset utilisation, and a reduction in human mistakes. This research highlights AI's potential for cost-effectiveness in logistics, bolstering the rising trend towards automated and intelligent logistics procedures as a way to increase operational and financial efficiency.
Last but not least, the research finds that organisational culture both moderates and strengthens the association between AI adoption and logistical performance outcomes (H4). According to this research, a culture that is supportive is crucial to optimising the advantages of AI adoption. Because workers are more likely to be receptive to new technologies and when there is a higher emphasis on continuous development, organisations with an innovation-oriented culture are better positioned to incorporate and use AI technology efficiently. This finding is in line with organisational behaviour research, which highlights the importance of culture in the success of technology adoption. It implies that companies looking to use AI should think about fostering an innovative culture to optimise performance gains.

Conclusion:

The research highlights the influence of organisational elements and cutting-edge technology on performance results by demonstrating substantial, statistically significant connections among important variables in logistics operations.
The average age of the respondents was 2.11 (SD = 1.09), which indicates significant variation. Age also has a positive correlation with years of experience ($r = 0.527$, $p < 0.01$) and job role ($r = 0.442$, $p < 0.01$). This suggests a connection between experience and job development in logistics, since older workers often hold higher positions and have more expertise.

With a mean of 1.45 (SD = 0.50), the distribution of genders is balanced. However, there is a tiny negative connection between gender and education ($r = -0.147$, $p < 0.05$) and years of experience ($r = -0.124$, $p < 0.05$), suggesting that there are minor gender-related disparities in these domains.
Age, experience, and education level are significantly positively correlated with the diversity of work tasks, as shown by a mean of 2.40 (SD = 0.91; $r = 0.442$, $p < 0.01$). People that work in senior positions are often older, more seasoned, and have more education.
With a mean of 2.75 (SD = 1.37), years of experience is highly associated with education ($r = 0.713$, $p < 0.01$), as well as with the adoption of AI ($r = 0.157$) and current analytics ($r = 0.231$, $p < 0.01$). This

implies that seasoned personnel are more inclined to use cutting-edge logistics technology. Operational efficiency is greatly increased by advanced analytics (estimate = 0.658, $p < 0.001$). Given the substantial positive association with operational efficiency ($r = 0.641$, $p < 0.01$), this study supports the notion that analytics integration enhances logistical performance.

The idea that AI lowers costs is supported by the fact that its use successfully lowers logistics costs (estimate = 0.669, $p < 0.001$). AI's ability to increase efficiency is shown by the strong correlations between its installation and cost reduction ($r = 0.733$, $p < 0.01$).

According to the moderation analysis, the association between AI adoption and logistics performance outcomes is strengthened by an innovation-oriented organisational culture (moderation effect = 0.343, $p < 0.001$). It has been shown that organisational culture is essential to optimising the advantages of AI for logistics, with a substantial positive connection ($r = 0.731$, $p < 0.01$). This suggests that businesses that deploy AI and have a supportive culture have higher performance gains.

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