Challenges and Opportunities of Artificial Intelligence on Supply Chain Management: A Case of Delta Beverages, Zimbabwe.

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ABSTRACT

This study examines the challenges and opportunities presented by Artificial Intelligence (AI) in the supply chain management (SCM) of Delta Beverages. The objectives were to identify critical factors influencing AI adoption, assess its impact on financial performance, and propose policy reforms to support effective integration. The study is guided by two theories namely the Resource based View and Technology-Organisation-Environment. A mixed-methods approach, grounded in both positivist and interpretivist research philosophies, was employed. Data were collected from 80 respondents through structured questionnaires with a five-point Likert scale, 20 semi-structured interviews, and direct observations. Findings revealed that AI significantly enhances demand forecasting, inventory management, predictive maintenance and real-time logistics decision-making, thereby improving operational efficiency and reducing costs. However, challenges persist, including limited supply chain visibility due to data quality issues, a shortage of skilled personnel, integration difficulties, employee resistance to change, high initial investment costs and uncertainty regarding return on investment (ROI). The research has led to the conclusion that despite AI having the potential to revolutionize Delta Beverages' supply chain, its implementation will be successful only if skill gap issues, data governance challenges and costs are taken care of. Some of the most effective recommendations that can be made in this regard would be implementing effective AI training programmes within the organization, developing better data management processes, utilizing incentives provided by governments and industries for seamless integration and implementing effective change management approaches, among others.

Keyterms: Artificial Intelligence, Supply Chain Management, Challenges, Opportunities

INTRODUCTION

In the current highly competitive market, where customers want high-quality products and services with narrow profit margins and quick turnaround times, businesses must take advantage of every possible opportunity to enhance their operations. Enhancing the supply chain efficiency and adaptability to fluctuations in the unpredictable business world is crucial for maintaining a company's commercial competitive excellence in an ever-changing business (Ivanov and Dolgui, 2020). In a number of industries, AI has become a catchword that could be among the most often used terms in both commercial and research domains. McCarthy introduced AI in 1956. While some see AI as a gateway to a world of opportunity, others predict that AI will result in job losses and an increase in employee layoffs (Dwivedi, Hughes, Coombs, Constantiou, Duan, Edwards and Upadhyay, 2021). It is anticipated that these discussions will continue between the two sides until individuals understand the advantages of AI, how it will improve their lives, and how it will not only make their businesses run more smoothly and quickly but also assist them in their daily lives.

Background To the Study

AI has revolutionised many industries worldwide and given the diversity and dynamic nature of African nations, its possible effects on supply chain management are particularly intriguing. African nations' supply chain

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dynamics are influenced by a wide range of elements, such as their diverse economies, poor infrastructure and particular market circumstances. The potential for overcoming these obstacles, increasing efficiency and accelerating sustainable growth exists in the integration of AI and machines with supply chain management. Research conducted by Wamba, Queiroz and Trinchera (2021) explored the application of AI in logistics optimisation within the automotive supply chain, demonstrating how AI algorithms could enhance efficiency in warehousing, inventory management and transportation. In the United Kingdom, Dubey and others (2021) highlighted how AI-driven predictive analytics improved demand forecast accuracy, enabling retailers to optimise inventory levels. Research in Sweden by Andersson and Eriksson (2021) illustrated how the combination of blockchain and AI enhanced transparency, traceability, and data-driven decision-making in the Swedish supply chain.

AI is significantly changing several sectors. By using information technology (IT) systems, it is possible to identify patterns in already-existing databases and algorithms, which facilitates the provision of suitable solutions and informs the process of making decisions. Feizabadi (2020) and Toorajipour and others (2021) are part of the many scholars who have lately researched this subject and released academic papers on it. Their research aimed to clarify how AI contributes to supply chain management studies based on a systematic review literature of 64 relevant publications. An effective supply chain management system must guarantee a cost-effective, flexible and continuous flow of resources and products at all times. The dynamic settings in which businesses operate are subject to significant risks of disruptions from unforeseen and unusual occurrences, such as natural catastrophes, fluctuations in demand and changes in government policies. Dynamic environments highlight the need to change the current supply chain to be more resistant against interruptions and be more flexible, resilient and able to recover (Dolgui and Ivanov, 2021; Ivanov and Das, 2020).

AI solutions can help African supply chains overcome important obstacles. For example, AI-driven route optimisation technologies can lower transportation costs and increase delivery efficiency in Nigeria (Smith, 2020). In South Africa, demand forecasting driven by AI can lessen the effect of varying market circumstances on inventory management (Chironga, De Grandis, Mylenko and Zouaoui, 2020). AI-based demand forecasting in Kenya has enabled shops to better react to customer trends and reduce stockouts (Mwangi and Kamau, 2021). Furthermore, reduced post-harvest losses have resulted from the use of AI in Ethiopian agricultural supply chain route planning (Tesfaye, Tadesse and Zegeye, 2022). In Ghana, blockchain technology and AI have been applied to track and verify the provenance of agricultural goods, resolving issues with food safety and quality (Appiah et al., 2020).Research on AI's effects on SCM in Zimbabwe appears to be lacking at the moment. Although the topic of supply chain management research powered by AI is growing worldwide, there is a discernible lack of discourse on the Zimbabwean context. Comprehending these subtleties may facilitate customised approaches to efficiently utilise AI in Zimbabwe's distinct economic and logistical environment.

Research Questions

- What specific opportunities and challenges does Delta Beverages encounter in implementing AI within its supply chain management processes?
- What are the key factors influencing the adoption of Artificial Intelligence at Delta Beverages?
- How can the incorporation of Artificial Intelligence influence the financial performance of Delta Beverages?
- What policy reforms can be identified and implemented to promote and enforce the adoption of AI in supply chain management?

LITERATURE REVIEW

AI Concept

Artificial Intelligence (AI), a term attributed to John McCarthy and traceable to the 1956 Dartmouth workshop, has experienced substantial growth since the early 2000s, prompting re-evaluation across academic fields and industries. AI integrates scientific and engineering disciplines (including economics, philosophy, mathematics,

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cognitive science, neurology and linguistics) to replicate human behaviour and resolve practical problems (Marcus, Davis & Gureckis, 2020). While mathematics formalises, these rules using algorithms and probability, philosophy aids in our understanding of ML and rule-based processes. Understanding how computers learn is aided by cognitive science, which studies human cognitive processes. While neuroscience clarifies brain function and draws parallels between the workings of the human brain and computers, linguistics investigates the relationship between language and the mind. Collectively, these have aided the creation of intelligent machines capable of understanding their environment and acting logically (Russell, Norvig, & Davis, 2022; Marcus, Davis, & Gureckis, 2020).

As an interdisciplinary field spanning computer science and data science, AI encompasses systems that learn from vast historical data and independently identify patterns to form conclusions (LeCun, Bengio & Hinton, 2021). Its key subfields include Machine learning (ML), neural networks, natural language processing (NLP), expert systems, robotics, and machine vision (Duan, Edwards & Dwivedi, 2021). The current surge in AI adoption is driven by three key factors: increased computing power, greater data availability and innovative algorithms enabled by maturing cloud infrastructure and growing data volumes (Brynjolfsson, McElheran, & Nanda, 2021).

ML lies at the core of AI, enabling systems to identify data patterns, make decisions and improve over time with minimal human intervention (Brynjolfsson & McAfee, 2021). Artificial neural networks (ANNs), modelled on the human nervous system, process abstract information and learn from examples. Expert systems analyse large data sets to support decision-making, including demand management in supply chains (Russell & Norvig, 2021).

Artificial Intelligence and Supply Chain Management

Supply chain management (SCM) coordinates three key flows, products from suppliers to customers, money from customers to suppliers and information between all parties, across an integrated network of businesses, resources, and services (Stefanovic and Stefanovic, 2021). AI-powered supply chain management enables autonomous, self-learning decision-making even in partially unknown environments (Validi et al., 2020). Soleimani (2021) identifies four supply chain management application areas for AI: prediction, modelling and simulation, decision support and optimisation. Forecasting, inventory management, revenue management and marketing, transportation, supply chain management and risk analysis are the six domains that Choi and others (2022) describe as using big data and ML methodologies in operations management. All of these fields have an intersection with AI.

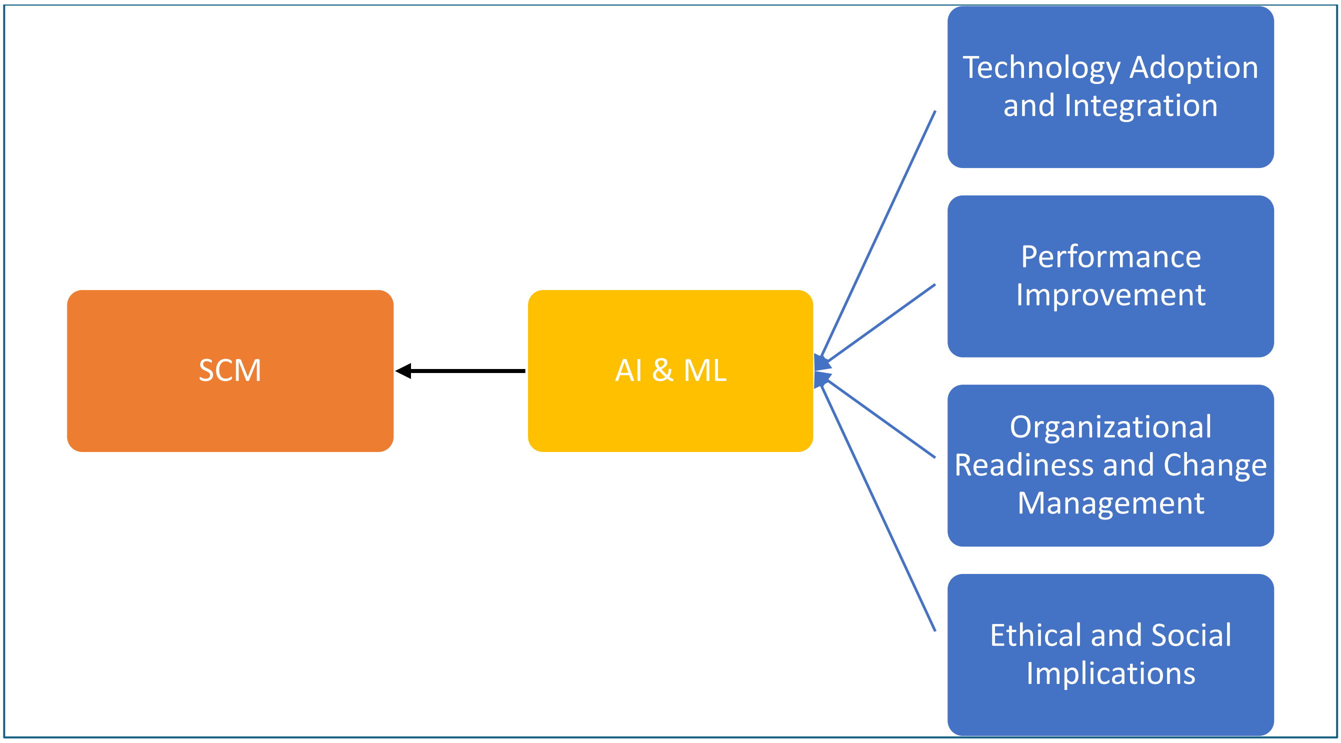
The supply chain industry has been greatly impacted by these innovative technologies. Walmart exemplifies AI's impact in retail supply chain Management, using its Social Genome Big Data analytics system to analyse social media activity and deliver personalised product recommendations (Roden et al., 2020). Effective AI systems combine artificial and human intelligence across three process stages: monitoring via IoT devices, analysis through advanced analytics and action based on data-driven insights. Businesses employ Internet of Things (IoT) devices to track products and activities in real-time, analyse collected data using advanced analytics to provide insights that can be put into practice and then take appropriate action based on these insights to increase productivity (Baryannis et al., 2023).

Developing and Deploying AI Models in Supply chain Management

According to Davenport (2020), AI sets itself apart from conventional rule-based software programming by enabling computers to create and train models, design features, change parameters, rebuild models and continuously learn and adapt. AI techniques are commonly employed to extract valuable insights from data, giving systems the ability to learn and adapt on their own using historical data (Lee et al., 2022). Recognising AI's capacity for data processing, learning, training and information storage is essential (Singh and Challa, 2023). Successful AI deployment requires gathering vast volumes of high-quality data and carefully selecting data sources to enable accurate results and decision-making through AI training, utilising infrastructure that supports the use of AI, as well as data sources pertinent to supply chain management.

Conceptual Framework

Figure 1: Conceptual Framework



Source: Researchers' compilation, 2026.

The conceptual framework maps the relationship between AI and ML adoption (independent variables) and SCM performance (dependent variable), with three independent variable dimensions:

- Technology adoption and integration: the extent of AI and ML use across SCM operations.
- Organisational readiness and change management: the capacity to adapt culture, structures, and processes.
- Ethical and social considerations: ensuring responsible, transparent and fair AI and ML practices.

The dependent variable SCM performance, is measured through demand forecasting accuracy, inventory optimisation, supply chain visibility, predictive maintenance and real-time logistics decision-making. The framework assumes a direct causal relationship: greater AI and ML adoption drives improved supply chain performance, creating a positive feedback loop that reinforces further innovation and competitive advantage. Applied to Delta Beverages, this framework guides the analysis of how AI and ML adoption translates into measurable supply chain improvements.

Contextual Analysis

Empirical research consistently highlights data quality and organisational resistance as the primary barriers to AI and ML adoption in SCM. Shrivastav (2022) found data quality to be a major obstacle in real-world AI logistics deployments, while Younis and others (2022) identified similar challenges in healthcare SCM, emphasising that accurate, complete data is essential for effective AI and ML applications. Ivanov (2020) similarly stressed the centrality of high-quality data.

In the African context, additional barriers include infrastructure limitations, economic disparities and the digital divide. Mwamburi and Njenga (2020) found that financial constraints particularly hinder SMEs in East Africa from investing in AI and ML systems. Abioye and others (2021) demonstrated that AI and ML systems trained on local data can significantly improve demand forecasting accuracy in Southern Africa. Kamau and Mutua (2018) highlighted the role of government-private sector collaboration in accelerating adoption, including policy incentives that have enabled successful joint initiatives.

Collectively, the literature underscores the need for context-sensitive, mixed-methods research approaches to fully understand the dynamics of AI and ML integration in supply chain management. These insights inform strategic decision-making as organisations navigate the opportunities and challenges of these transformative technologies.

The hypothesis posits a significant relationship between Artificial Intelligence and supply chain management (SCM). The literature provides theoretical and empirical grounding but also reveals nuances requiring critical synthesis. Artificial Intelligence's interdisciplinary roots establish capacities for pattern recognition and autonomous learning (Marcus, Davis and Gureckis, 2020; LeCun, Bengio and Hinton, 2021), aligning with supply chain management 's core coordination functions (Stefanovic and Stefanovic, 2021). Artificial Intelligence applications map to supply chain management domains like prediction and optimisation (Soleimani, 2021; Choi et al., 2022), with examples such as Walmart's Social Genome (Roden et al., 2020). However, the relationship is not automatic; barriers like data quality, organisational resistance and contextual factors (for example, infrastructure limitations in Africa) moderate its strength and direction (Shrivastav, 2022; Mwamburi and Njenga, 2020). The conceptual framework operationalises this through three mediating dimensions are technology adoption, organisational readiness and ethical considerations suggesting the hypothesis should be tested as a conditional, not purely direct, association. Thus, while the literature supports a significant positive relationship, effect sizes may vary across contexts, reinforcing the need for hypothesis testing that accounts for moderating and mediating variables. The following review presents the evidence base for this hypothesis.

Theoretical Framework

There are various theories that researchers can apply to this study but the most relevant ones are the Technology-Organisation-Environment (TOE) Framework and the Resource-Based View (RBV) of the firm. These theories provide a robust lens for understanding the multifaceted dynamics of Artificial Intelligence adoption in a developing country context.

Technology-Organisation-Environment (TOE) Framework

The TOE framework, originally developed by Tornatzky and Fleischer (1990) and extensively refined by subsequent scholars, posits that technology adoption is influenced by three contextual dimensions, that is the technological context, organisational context and environmental context. The technological context refers to the internal and external technologies relevant to the firm, including their availability and characteristics. The organisational context encompasses firm-level attributes such as size, scope, managerial structure and readiness for change. The environmental context includes the industry structure, regulatory environment and competitive pressures.

Current research has applied the TOE framework to Artificial Intelligence adoption in supply chain management. Awa, Ojiabo and Emecheta (2020) demonstrated that technological readiness, top management support and competitive pressure significantly predict Artificial Intelligence adoption in Nigerian manufacturing firms. Similarly, Alsheibani, Cheung and Messom (2019) found that organisational readiness and perceived benefits are critical determinants of Artificial Intelligence adoption among Australian organisations. In the African context, Mwangi and Ochieng (2021) applied the TOE framework to examine cloud computing adoption in Kenyan supply chains, revealing that infrastructure limitations and regulatory uncertainty are major environmental barriers.

For Delta Beverages, the TOE framework is particularly relevant. The technological context captures the availability of Artificial Intelligence tools suitable for beverage supply chain operations, including demand forecasting and inventory optimisation systems. The organisational context addresses Delta Beverages' internal capacity for change, including employee skills, management commitment and cultural readiness. The environmental context encompasses Zimbabwe's regulatory landscape, economic volatility and infrastructure constraints that shape the feasibility of Artificial Intelligence deployment.

Resource-Based View (RBV) of the Firm

The Resource-Based View, pioneered by Barney (1991) and extended by contemporary scholars, argues that firms achieve competitive advantage through resources that are valuable, rare, inimitable and non-substitutable. In the context of Artificial Intelligence, data assets, algorithmic capabilities and organisational learning processes represent strategic resources that can distinguish firms in supply chain performance.

Recent studies have extended RBV to the Artificial Intelligence domain. Gupta and George (2020) proposed the concept of "Artificial Intelligence capability" as a firm-level resource comprising data infrastructure, algorithmic skills and integration capabilities. They found that firms with superior Artificial Intelligence capabilities achieve significantly higher supply chain agility and cost efficiency. Artificial Intelligence resources are most valuable when combined with complementary organisational resources such as data-driven culture and cross-functional collaboration (Mikalef, Pappas and Krogstie, 2020).

In the supply chain environment, Artificial Intelligence-enabled analytics capabilities serve as strategic resources that enhance demand forecasting accuracy and inventory optimisation (Dubey, Gunasekaran and Childe, 2019). According to Wamba, Gunasekaran and Akter (2020) found that big data analytics capabilities, underpinned by Artificial Intelligence, contribute to supply chain performance by enabling real-time visibility and predictive decision-making.

The RBV perspective at Delta Beverages highlights that successful Artificial Intelligence adoption depends not only on technology acquisition but also on expanding internal capabilities that are challenging for competitors to replicate. These include exclusive data on Zimbabwean consumer behaviour, trained personnel who understand local market dynamics and organisational routines that integrate Artificial Intelligence insights into daily operations.

The TOE framework and RBV are complementary for this research because it elucidates the external and internal conditions that enable or constrain Artificial Intelligence adoption at Delta Beverages, while RBV explains how Artificial Intelligence can serve as a source of sustained competitive advantage once adopted. Combined, they provide a comprehensive theoretical foundation for examining both the challenges and opportunities of Artificial Intelligence in supply chain management at Delta Beverages, Zimbabwe.

RESEARCH METHODOLOGY

Research Design

This study adopted a mixed-methods approach, integrating both quantitative and qualitative techniques to provide a comprehensive understanding of the opportunities and challenges of AI adoption in supply chain management (SCM) at Delta Beverages. The methodological design was guided by a pragmatic research philosophy, allowing for both statistical analysis of patterns and relationships, as well as an in-depth exploration of participant perceptions and organisational experiences.

Population, Sampling and Data Collection

From a target population of 150 employees from Supply Chain Management, Information Technology, Operations, Executive Leadership and Accounts departments, 80 structured questionnaires (quantitative) were collected and 20 qualitative semi-structured interviews were conducted with middle and senior managers from Delta Beverages, Bulawayo. The target departments have technical as well as operationally relevant knowledge and experience in AI-related supply chain management activities. In addition, direct observations provided real-time insights into operational workflows, facilitating triangulation of data sources for enhanced validity.

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The sample size of 80 questionnaire respondents was determined using Slovin's formula ($n = N / (1 + Ne^2)$), where N = 150 and a margin of error e = 0.05, yielding a minimum sample of approximately 109. A purposive sampling strategy was adopted, to prioritise respondents with direct knowledge of and involvement in AI-related SCM activities, resulting in 80 usable responses — representing a 53% response rate from the target population. This purposive approach is consistent with the study's interpretivist dimension, which prioritises depth and relevance of insight over statistical representativeness (Saunders, Lewis, and Thornhill, 2019). The 20 semi-structured interviews were selected to achieve thematic saturation, with participants drawn from middle and senior management levels across the five target departments.

Data Collection Methods

- Structured Questionnaires – Measured perceptions of AI's impact on SCM using a five-point Likert scale (1 = Strongly Agree, 2 = Agree, 3 = Neutral, 4 = Disagree, 5 = Strongly Disagree), covering both independent and dependent variables in the conceptual framework. Under this inverted scale, mean scores below 2.5 indicate general agreement, scores around 3.0 indicate neutrality and scores above 3.5 indicate disagreement. All mean scores reported in this study are interpreted accordingly.
- Semi-Structured Interviews – Explored nuanced organisational realities, enabling deeper analysis of challenges, opportunities and adoption factors.

Data Analysis

Data from questionnaires were processed using Statistical Package for the Social Sciences (SPSS) version 21. Descriptive statistics (frequencies, means, modes and standard deviations) were used to summarise responses and visual presentations such as tables, bar charts and pie charts were used to illustrate findings. Interview transcripts and observation notes were subjected to thematic analysis, identifying recurring patterns, themes and underlying meanings. The quantitative results provided measurable evidence of AI's effects, while qualitative insights contextualised these results within the operational realities of Delta Beverages.

FINDINGS AND DISCUSSIONS

Results from interviews and questionnaires are discussed in detail below.

Demographic Information

Respondents were asked to indicate their years of experience as indicated in Table 1 below.

Table 1: Delta Beverages employees' experience

Years	**< 5 Years**	**6 - 10 years**	**11 - 15 years**	**16 - 20 years**	**> 21 Years**
Frequency	35	29	10	4	2
%	44%	36%	13%	5%	3%

Source: Field Survey, 2026

Table 1 shows that the majority of respondents (44%) had worked at Delta Beverages for 10 years or less, with 36% having under 5 years' experience and 13% between 6–10 years. Those with 11–15 years accounted for 13%, 16–20 years for 5% and over 21 years for only 3%. This distribution suggests a relatively young and mid-career workforce, which may influence openness to technological change and AI adoption.

Table 2: Delta Beverages Respondents' Academic Qualifications

Qualifications	**Masters**	**Bachelors**	**Diploma**	**Certificate**	**Advanced level**	**Ordinary level**
Frequency	27	34	14	5	-	-
%	34%	43%	17%	6%	-%	-%

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Table 2 indicates that 43% of respondents held bachelor's degrees, 34% had master's degrees, 17% had diplomas and 6% had certificates. The absence of respondents with only Ordinary or Advanced Level qualifications reflects a highly literate and professionally qualified workforce, a factor likely to facilitate AI-related training and implementation.

Impact of AI on Supply Chain Management

The study's main objective was to determine the impact of AI on supply chain management. Respondents were asked to express their views on the impact of AI on supply chain management using a five-point Likert scale (1 = Strongly Agree to 5 = Strongly Disagree).

Table 3: Response to the effects of the impact of AI on Supply Chain Management

Variables	Mean	Mode	Std. Deviation	Range
Improve demand forecasting accuracy	2.2714	2	1.0204	4
Optimise inventory management processes	2.4143	2	1.1856	4
Enhance SC visibility and transparency	2.6429	3	1.0220	3
Facilitate predictive maintenance in manufacturing facilities	2.2571	2	0.9881	4
Enable real-time monitoring and decision-making in logistics	2.5143	2	1.1640	4

Source: SPSS Results, 2026

Respondents agreed that AI positively impacted demand forecasting accuracy (mean 2.2714), inventory management optimisation (mean 2.4143), predictive maintenance (mean 2.2571) and real-time logistics decision-making (mean 2.5143). Supply chain visibility and transparency scored closest to neutral (mean 2.6429, mode 3), reflecting more mixed experiences and highlighting the importance of strong data governance frameworks. Overall, AI's impact across all five supply chain dimensions was viewed positively, though variability in responses indicated differing levels of implementation success across departments.

Challenges Encountered by Delta Beverages in Implementing AI within its Supply Chain Management Processes

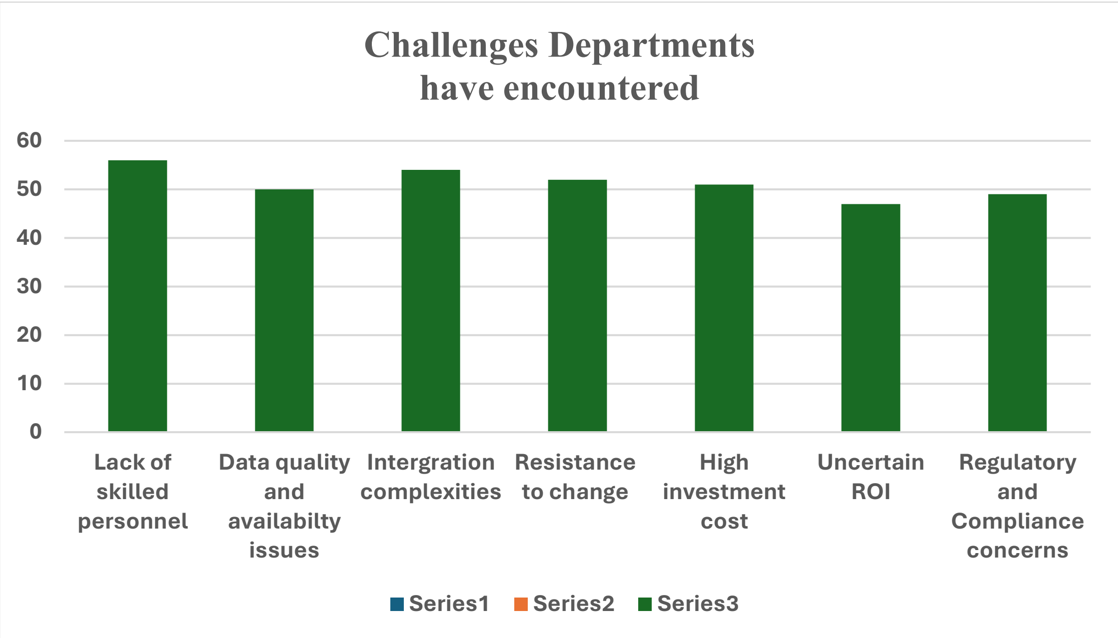

Figure 2: Challenges faced in the adoption of AI in supply chain management

Source: Field Survey, 2026

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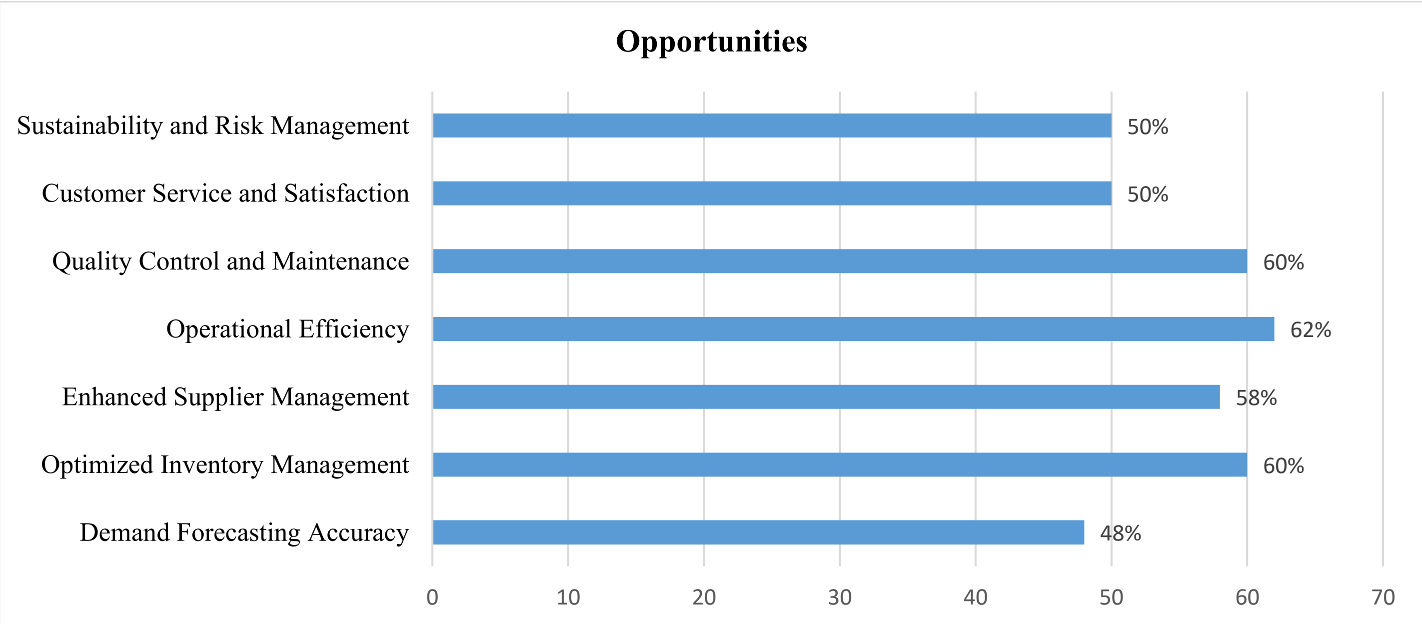
NB* All challenges are out of the total sample size of 80

The findings show that Delta Beverages' departments faced several significant challenges when implementing AI in supply chain management. The most common challenge, reported by 56 of respondents, is a shortage of skilled personnel, highlighting the critical need for AI expertise. Poor data quality and availability was reported by 50 respondents, integration issues with existing systems were reported by 54 respondents, employee resistance to change was reported by 52 respondents, high initial investment costs were reported by 51 respondents, uncertain ROI was reported by 47 respondents and 49 respondents reported regulatory and compliance concerns as significant barriers. Collectively, these challenges underscore the importance of a strategic and comprehensive approach to AI implementation.

The conclusions derived from the quantitative analysis can be further supported with the help of the qualitative data obtained from interviews conducted, revealing a rather ambiguous attitude towards the application of AI. As mentioned by interviewees, the role of AI in inventory management is double-sided, as AI-based systems proved useful in achieving dynamic inventory optimization, yet the combination of those technologies with other company systems is still a major problem that needs to be addressed. It should be noted that the majority of people interviewed (18 out of 20) expressed their views on the potential of AI in reducing costs related to inventory maintenance, as well as enhancing the resilience of supply chains through better demand prediction. Nevertheless, there were some doubts concerning high implementation and subsequent maintenance expenses associated with AI usage.

Opportunities of Artificial Intelligence in Supply Chain Management

Figure 3: Opportunities of AI on Supply Chain Management



Source: Field Survey, 2026

The survey revealed strong recognition of AI's opportunities across key supply chain functions. Sixty-two percent (62%) of respondents recognised AI's contribution to operational efficiency, while 60% acknowledged its impact on both inventory optimisation and quality control and predictive maintenance. Fifty-eight percent (58%) saw AI's value in supplier management, 50% in improved customer service and sustainability and risk management, and 48% in enhanced demand forecasting accuracy. These findings demonstrate AI's broad transformative potential across Delta Beverages' supply chain operations.

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Key Factors Influencing the Adoption of Artificial Intelligence at Delta Beverages

Table 4: Factors Affecting AI Adoption

Key factors influencing the adoption of Artificial Intelligence at Delta Beverages

Variables	Mean	Mode	Std. Dev
Leadership Support and Commitment	2.3571	2	1.0906
Data Quality and Availability	2.3429	2	1.1019
Organisational Culture and Readiness for Change	2.2571	2	1.0312
Skills and Talent	2.1714	2	1.1030
Budget and Financial Resources	2.3000	2	1.0680
Regulatory Environment and Compliance Requirements	2.2000	2	1.0158
Technology Infrastructure	2.1286	2	0.9619
Industry Standards and Best Practices	2.1286	2	1.0621
Risk Management and Security	2.2714	2	1.0204
Vendor Selection and Partnerships	2.2429	2	1.0277

Source: SPSS Results, 2026

Analysis of the factors influencing AI adoption revealed broad consensus across all ten variables, with all modes at 2 (agree) and means ranging from 2.13 to 2.36. Leadership support, data quality, organisational culture, skills and talent, financial resources, regulatory compliance, technological infrastructure, industry standards, risk management and vendor partnerships were all identified as important. The relatively low variability in most variables indicated a shared organisational understanding of what is required for successful AI adoption. Addressing these factors comprehensively and strategically is critical for Delta Beverages to fully realise AI's potential while mitigating associated challenges.

How the Incorporation of AI has Influenced the Financial Performance of Delta Beverages

Table 5: The impact of AI on the Financial Performance of Delta Beverages

Variables	Mean	Mode	Std. Dev
Cost Reduction	2.4429	2	0.987395
Revenue Growth	2.4000	2	1.055009
Improved Profit Margins	2.2571	2	0.973351
Enhanced Productivity	2.3857	2	1.145791
Better Investment Decisions	2.3857	2	0.982349
Competitive Advantage	2.3000	2	1.012244
Compliance and Regulatory Compliance	2.2571	2	1.002688
Reduced Financial Risk	2.3714	2	1.037995
Optimised Resource Allocation	2.3571	2	1.049993
Fraud Detection and Prevention	2.3143	2	0.956183

Source: SPSS Results, 2026

Respondents generally agreed that AI positively influenced all ten financial performance dimensions. Cost reduction (mean 2.4429) and revenue growth (mean 2.4000) received the strongest agreement, while improved profit margins and regulatory compliance (both mean 2.2]571) were also consistently recognised. Moderate variability on productivity (std dev 1.1458) and competitive advantage (std dev 1.0122) suggested that the full benefits of AI have not yet been uniformly realised across the organisation, identifying areas for further strategic development.

A notable pattern in Table 5 warrants methodological transparency. All ten variables share an identical mode of 2 (Agree) and the range between the highest mean (2.4429) and lowest mean (2.2571) is only 0.188 — a narrow spread for ten conceptually distinct financial constructs. This uniformity is consistent with acquiescence bias, a well-documented phenomenon in Likert-scale research whereby respondents systematically select agreement responses across items without fully discriminating between them (Saunders, Lewis, and Thornhill, 2019). This bias may be particularly pronounced in organisational survey settings where employees associate positive AI perceptions with organisational expectations. Accordingly, the financial performance findings should be interpreted as indicative of general positive sentiment towards AI rather than as precise measures of financial impact. Future research should triangulate these perceptions with objective financial data from Delta Beverages' internal records, such as documented cost savings, inventory reduction figures and audited efficiency gains.

The qualitative data analysis revealed that 15 out of 20 respondents at Delta Beverages agree on the positive impact of AI technology across multiple organisational dimensions. Employees recognised AI as critical for cost savings, revenue growth and profit margin improvements. AI's role in streamlining operations, reducing manual labour and optimising resource utilisation was highlighted for its cost-cutting benefits. Similarly, AI was seen to drive revenue growth through improved customer engagement and personalised marketing strategies, though the extent of these benefits varied by sector of the organisation.

The use of AI was also recognised for increasing productivity and making better investment decisions. Employees agreed that AI improves productivity by automating repetitive tasks and enabling precise decision-making, though the degree of impact varies by department. The advanced analytics and insights provided by AI were perceived to improve investment decisions, though the benefits were not universally realised, indicating room for further optimisation. Furthermore, AI was identified as a critical factor in gaining a competitive advantage, adhering to regulations and minimising financial risks. Respondents emphasised AI's role in differentiating Delta Beverages in the market, ensuring regulatory compliance and mitigating financial threats via advanced risk management capabilities. The consistency of responses regarding compliance and fraud prevention demonstrates the widespread acceptance of AI's importance in these fields.

The inclusion of fraud detection and prevention as a financial performance variable (mean 2.3143, std dev 0.9562) requires specific comment. This variable produced the lowest standard deviation in Table 5, indicating the highest level of response consensus, yet it does not feature in any of the qualitative interview narratives and was not identified as a priority area in the challenges or opportunities findings. This disconnects between the quantitative consensus and the absence of qualitative corroboration suggests that respondents may have answered this item on autopilot rather than from direct operational experience of AI-driven fraud prevention at Delta Beverages. While AI does have genuine applications in financial fraud detection — particularly in procurement, invoice processing and supplier payment monitoring (Roden et al., 2020) — the current study cannot substantiate this specific benefit within Delta Beverages' supply chain management context. This item should be treated with caution and explored more rigorously in future research.

Policy Reforms to Promote and Enforce the Adoption of AI in Supply chain Management

Table 6: Policy Reforms

Variable	Mean	Mode	Std. Dev
Government Incentives	2.5143	2	0.9890
Industry Standards and Guidelines	2.4714	2	0.9887
AI Education and Training Programs	2.3714	2	0.9657
Ethical Guidelines for AI Uses	2.3000	2	1.0815
Regulatory Compliance Frameworks	2.3143	2	0.9254
Procurement Policies and Vendor Selection Criteria	2.2143	2	0.9308

Source: SPSS Results, 2026

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Respondents agreed on the importance of all six policy reform dimensions. Government incentives (mean 2.5143) and industry standards and guidelines (mean 2.4714) were seen as the most critical enablers. AI education and training programmes (mean 2.3714), regulatory compliance frameworks (mean 2.3143), ethical guidelines (mean 2.3000), and procurement policies and vendor selection criteria (mean 2.2143) were also broadly supported. The consistently low standard deviations across these variables indicated widespread organisational recognition of the policy environment required to facilitate successful AI integration.

The findings from the 16 out of 20 interviews highlighted the importance of several factors in facilitating AI adoption in Delta Beverages' supply chain management. Government incentives emerged as significant enablers, implying that financial assistance, such as tax breaks and subsidies, can help overcome barriers to AI adoption. The significance of industry standards and guidelines was also emphasised, implying that standardised protocols are critical for ensuring seamless and consistent AI integration. Education and training programmes were widely recognised for their role in providing employees with the necessary AI skills, resulting in a competent and adaptable workforce.

The qualitative data analysis revealed significant insights into the impact of AI on supply chain management at Delta Beverages. AI's transformative potential in demand forecasting, inventory management, supply chain visibility, predictive maintenance, logistics operations and organisational culture was evident. Ten out of 20 Respondents emphasised the importance of consistent data sources and strong data management practices to effectively support AI algorithms. An organisational culture that promotes innovation and embraces change was cited as critical for overcoming employee resistance to AI adoption.

Specific challenges faced by Delta Beverages in implementing AI within its supply chain management processes

Figure 4: Challenges in the Implementation of the Policy Reforms

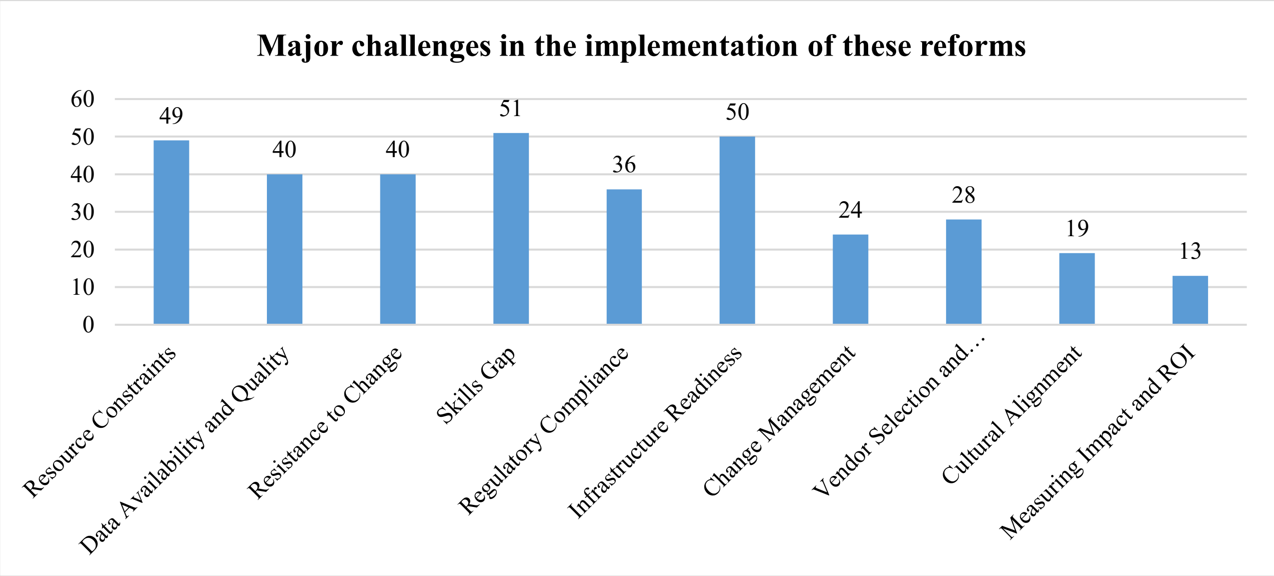

Figure Error! Use the Home tab to apply 0 to the text that you want to appear here.**.4 Challenges in the Implementation of the Policy Reforms**

NB* All challenges are out of the total sample size of 80

Source: Field Survey, 2026

The study identified the most prominent challenges in implementing AI policy reforms. Fifty-one respondents identified the skills gap as a challenge, infrastructure readiness was reported by 50 respondents and resource constraints by 49 respondents. Data availability and quality was reported by 40 respondents and resistance to change were also noted by 40 respondents, alongside regulatory compliance there were 36 respondents, vendor selection and partnerships had 28 respondents and lastly change management was reported by 24 Respondents. Cultural alignment and measuring impact and ROI were mentioned less frequently but remained relevant considerations. Collectively, these findings highlight the multifaceted barriers Delta Beverages faces in translating policy intent into operational AI adoption.

The significance of industry standards and guidelines was also emphasised by the qualitative data, implying that standardised protocols are critical for ensuring seamless and consistent AI integration. Education and training programmes were widely recognised for their role in providing employees with the necessary AI skills, resulting in a competent and adaptable workforce. The study also emphasised the importance of ethical guidelines to address concerns about data privacy, bias and transparency, thereby encouraging responsible AI use. Regulatory compliance frameworks were identified as critical for ensuring that AI technologies meet legal standards and thus reduce risks. Clear procurement policies and vendor selection criteria were deemed critical for acquiring dependable AI solutions and promoting successful AI projects.

Qualitative data revealed conflicting views about AI's impact on supply chain visibility. While AI analytics provided real-time insights into inventory levels and shipment statuses, challenges remained in integrating data from various sources throughout the supply chain. Respondents recognised AI's potential to improve transparency while emphasising the importance of strong data governance frameworks to ensure data accuracy and reliability. According to interviews, improving data integration capabilities could help AI reach its full potential in providing end-to-end visibility across Delta Beverages' supply chain operations.

Limitations

While this study provides valuable insights into the challenges and opportunities of AI and ML adoption in supply chain at Delta Beverages, several limitations should be acknowledged when interpreting the findings.

First, the study is based on a single-organisation case study, which limits the generalisability of the findings to other beverage companies or industries operating in different economic and infrastructural contexts. The experiences and perceptions of Delta Beverages’ employees may not be representative of the broader Zimbabwean manufacturing or FMCG sector.

Second, the quantitative data on both Supply chain impact and financial performance are entirely perception-based, derived from a five-point Likert scale. No actual financial performance metrics — such as cost savings, inventory reduction figures, or return on investment data — were obtained from Delta Beverages’ internal records. As a result, the financial performance findings reflect employee perceptions rather than objectively verified organisational outcomes. Future research should seek to corroborate survey-based findings with audited financial data and documented operational records.

Third, the financial performance data in Table 5 exhibits statistical patterns consistent with acquiescence bias. All ten financial performance variables share an identical mode of 2, and the total spread between the highest and lowest means is only 0.188 — unusually narrow for ten conceptually distinct constructs. Acquiescence bias, whereby respondents tend to agree with survey items regardless of their content, is a recognised limitation of Likert-scale instruments in organisational settings (Saunders, Lewis and Thornhill, 2019). This pattern reduces the discriminant validity of the financial performance findings and should caution against drawing strong causal inferences from Table 5 alone. The fraud detection and prevention variable, in particular, produced the highest consensus (lowest standard deviation of 0.9562) yet received no qualitative corroboration from the interview data, further suggesting that some respondents may not have engaged critically with this item.

Fourth, the study is cross-sectional in design, capturing data at a single point in time. AI and ML adoption is a dynamic and evolving process; a longitudinal study would provide richer insight into how the benefits and challenges of AI adoption change as implementation matures within the organisation.

Fifth, the use of self-reported questionnaire data introduces the risk of social desirability bias, where respondents may have provided responses, they perceived to be more favourable or acceptable rather than reflecting their true experiences and views. This risk is particularly relevant in questions relating to leadership support and organisational readiness for change.

Sixth, while a purposive sampling strategy was appropriate for the study's qualitative objectives, the resulting sample of 80 questionnaire respondents (53% of the target population) may underrepresent the views of employees in departments with lower AI exposure, potentially skewing findings towards more AI-positive perspectives. Future research should consider larger, randomly sampled populations across multiple organisations to enhance the validity and transferability of findings.

RECOMMENDATIONS

Arising from the data analysis and findings, the following recommendations are proposed:

1. Improve AI Training and Skill Development: Delta Beverages should invest in comprehensive AI training and education programmes to address the skills gap identified in the study. Workshops, certification courses and collaborations with educational institutions could all be used to ensure that employees have the skills they need to use AI effectively.

2. Improve Data Management Practices: Delta Beverages should prioritise developing strong data management frameworks, as data quality and availability play a crucial role in AI adoption. This entails implementing advanced data collection, storage, and processing systems, as well as establishing clear data governance policies.

3. Utilise Government Incentives and Industry Standards: To enhance AI integration, Delta Beverages should seek government incentives like tax breaks and grants. The company should collaborate with industry bodies to stay up to date on best practices and compliance requirements, reducing risks and ensuring ethical AI use.

4. Create Effective Change Management Strategies: Delta Beverages should create and implement effective change management strategies, such as clear communication plans, stakeholder engagement and ongoing support throughout the AI implementation process. By involving employees in the change process and demonstrating the tangible benefits of AI, the company can create a more supportive and cooperative organisational culture.

5. Invest in AI-Ready Infrastructure: To address infrastructure challenges, Delta Beverages should upgrade its technology to support advanced AI applications. This includes updating hardware, software and network capabilities to meet the computational demands of AI technologies.

CONCLUSION

The key findings showed that AI significantly improved demand forecasting, inventory management, predictive maintenance and real-time logistics decision-making, resulting in increased operational efficiency and cost savings. The challenges included a lack of skilled personnel, poor data quality, integration issues and high initial investment costs. Conclusions highlighted AI's potential to transform supply chain management, emphasising the importance of addressing skill shortages, data quality issues and integration challenges for successful implementation. Strong leadership, effective data management and strategic investment were deemed critical.

Regarding financial performance, respondents generally perceived AI as contributing positively to cost reduction, revenue growth, profit margins and operational efficiency. However, these findings are based entirely on employee perceptions via a Likert scale instrument and exhibit statistical patterns consistent with acquiescence bias, including a uniform mode of 2 across all ten variables and a narrow mean spread of 0.188. These patterns reduce the strength of causal claims about AI's financial impact and underscore the need for future research to corroborate perceptual data with objective financial records. The fraud detection and prevention variable, in particular, lacked qualitative support and should be interpreted with caution.

Key recommendations included investing in AI training programmes, improving data management practices, taking advantage of government incentives and industry standards, developing comprehensive change management strategies, and upgrading technological infrastructure to support AI applications. These steps are critical for maximising AI's benefits and ensuring its successful integration into Delta Beverages' SCM processes.

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