

AI-Driven Administrative Automation in Internal Logistics: A Framework for Adoption and Organisational Transformation

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Abstract

Administrative processes in internal logistics are dominated by repetitive manual work, resulting in delays, fragmented information flow, and increased risks of errors. AI adoption is increasing in supply chain and manufacturing; however, its application to administrative tasks within internal logistics remains limited and is not well understood. This gap is addressed by developing a conceptual framework for the adoption of AI-administrative automation and validating it empirically in the South African manufacturing context. This is materialised by identifying the most suitable administrative tasks, assessing the effects on efficiency, accuracy, and speed, the challenges and risks of integrating AI automation into existing workflows, and the measurement and quantification of success. A mixed-methods design, consisting of a quantitative survey and qualitative semi-structured interviews, was adopted and grounded in a pragmatic approach. The findings indicate the suitability of structured, rules-based administrative tasks to automation. Concerns relating to trust, oversight, and accountability are also identified. The study concludes that AI-driven administrative automation constitutes a socio-organisational transformation shaped by behavioural, organisational, economic, and governance conditions, and proposes a framework to support responsible implementation.

Keywords

Internal logistics, Artificial Intelligence, AI-driven administration automation, AI Adoption Framework, South Africa

1. Introduction

Artificial intelligence (AI) has become a central theme in contemporary discussions on economic development, technological innovation, and organisational transformation. In global logistics and supply chain environments, researchers increasingly explore how AI enhances efficiency, accuracy, and responsiveness (Mohammed, 2024). Despite this rapid progress, existing research and industrial applications remain concentrated on physical logistics automation, such as transport routing, warehousing, and production scheduling, with considerably less attention given to administrative automation (Kaźmierczak et al., 2025). This imbalance has created a fragmented evidence base that overlooks the administrative processes underpinning operational performance.

Administrative functions within internal logistics, covering documentation, scheduling, reporting, and compliance, remain heavily reliant on repetitive manual input, which increases the potential for error and inefficiency. Studies

show that automation of such functions through AI can substantially improve accuracy and reduce process cycle times (Daio et al., 2025; Pelz-Sharpe, 2025). At the same time, persistent constraints relating to data quality, system interoperability, workforce readiness, and economic justification continue to hinder adoption (Teixeira et al., 2025). Within South Africa, these challenges are amplified by contextual constraints such as limited digital infrastructure, high logistics costs, skills shortages, and power instability (Mohammed, 2024). Although the automotive sector plays a significant role in the national economy, the adoption of administrative AI remains constrained by infrastructural, workforce, and organisational factors.

In synthesising existing research, three interrelated gaps become evident. First, a *conceptual gap* persists, as administrative processes remain substantially underrepresented in AI adoption literature compared with physical logistics automation. Second, a *contextual gap* is apparent, with limited empirical evidence originating from the South African logistics and automotive sectors, despite their operational scale and strategic importance. Third, an *evaluation gap* emerges because cost-benefit analyses rarely focus on administrative AI and frequently overlook indirect or intangible benefits. Together, these gaps underscore the need for a more integrated and contextually grounded understanding of AI-driven administrative automation.

1.1 Objective

Against this backdrop, this study investigates how AI-driven administrative automation can improve operational efficiency within internal logistics processes. By focusing on administrative rather than physical automation, the research addresses a gap in the existing literature.

This study examines the role of AI-driven administration automation in internal logistics within a South African manufacturing environment. The paper is structured as follows. Section 2 reviews relevant literature. Section 3 introduces the conceptual framework. Section 4 outlines the research method. Section 5 presents the quantitative and qualitative findings. Section 6 discusses the theoretical and practical implications. Finally, section 7 concludes the article and offers recommendations for future research.

2. Literature Review

2.1 Artificial Intelligence and Artificial Intelligence in Supply Chain Management

Artificial intelligence (AI) has become increasingly embedded across core supply chain management (SCM) functions. Literature show accelerating adoption across demand forecasting, inventory management, logistics optimisation, and procurement, with reported improvements in planning accuracy, stock control, network efficiency, and supplier management. Table 1 summarises these applications, outlining the benefits and challenges of AI use across major SCM domains, including data-quality dependencies and integration difficulties. Overall, the literature demonstrates that AI is generating tangible operational improvements across supply chain functions while also encountering persistent barriers that limit broader adoption.

Table 1. The applications, benefits, and challenges of AI use across primary supply chain management functions.

<i>SCM Function</i>	<i>Applications of AI</i>	<i>Illustrative Benefits</i>	<i>Key Challenges</i>	<i>Source</i>
<i>Demand Forecasting & Planning</i>	Use of ML and DL models for short- and long-term demand forecasting; integration of predictive analytics into planning systems.	AI reduces forecast errors by 20 – 30%, improving demand-supply alignment and reliability.	Data quality dependency: noisy or sparse datasets reduce accuracy.	Walter et al. (2025)
<i>Inventory Management & Optimisation</i>	Real-time stock control, automated replenishment decisions, integration with demand forecasts.	Improved order fulfilment rates and reduced excess stock; dynamic adjustment of inventory levels.	Integration with legacy ERP systems creates adoption bottlenecks.	Atwani et al. (2024)
<i>Logistics & Transportation Optimisation</i>	Route optimisation, load planning, vehicle scheduling, and network design incorporating sustainability factors.	AI-optimised routing reduces fuel costs by 5–10% and lowers CO ₂ emissions, while also improving logistics efficiency.	Requires real-time traffic, weather, and price datasets often unavailable to SMEs.	Mohammed (2024)

<i>Procurement & Supplier Management</i>	AI for supplier risk assessment, contract review, and automated supplier scoring.	Reduced supply disruptions through improved supplier selection and risk management.	Employee resistance due to mistrust of automated supplier scoring.	Guida et al. (2023)
<i>Cross-SCM Insights</i>	Systematic application of AI across forecasting, inventory, logistics, and procurement.	Consistent improvements in cost efficiency, agility, and service levels across SCM functions.	Skills shortages, high upfront costs, and ROI uncertainty hinder scaling.	Culot et al. (2024)

2.2 Adoption of new technologies

AI adoption in logistics depends on technical, organisational, behavioural, and economic factors that determine integration into workflows. While AI promises gains in forecasting, inventory, logistics optimisation, and procurement, success hinges on more than technical capability than cultural and organisational barriers who are equally influential (Daios et al., 2025). These dynamics shape the environment for administrative AI.

Technical and infrastructural challenges persist. Legacy ERP and WMS systems often lack interoperability with AI tools; poor data quality undermines reliability; and cybersecurity concerns deter adoption. Pilot projects may show value, but full-scale implementation exposes weaknesses in data pipelines and IT infrastructure (Richey et al., 2023). Financial and strategic constraints compound these issues. High costs for acquisition, integration, and maintenance, coupled with weak ROI frameworks, create uncertainty. Fewer than 20% of firms measure ROI systematically, a gap especially critical in resource-constrained settings where short-term pressures compete with long-term opportunities. Workforce readiness and culture further influence outcomes. Job-displacement fears, particularly in clerical roles, generate resistance (Combemale et al., 2025). Skills gaps in digital literacy and analytics limit effective interaction with AI systems, while entrenched routines slow behavioural adaptation. Adoption thus requires deliberate change management, transparent communication, and reskilling (Daios et al., 2025).

These complexities align with technology-acceptance models, which stress perceived usefulness and ease of use, and TAM2, which adds social influence and job relevance. Organisational-change frameworks reinforce the need for leadership alignment, communication, and shared vision to institutionalise new practices (Carreno, 2025).

Economic evaluation completes the adoption landscape. Cost-benefit analysis (CBA) compares adoption costs, including technology, integration, training, with benefits such as labour savings, error reduction, and cycle-time improvements (Havenga et al., 2022). Indirect benefits, such as better decisions, compliance, scalability, are harder to quantify but strategically significant. While warehouse automation studies show long-term gains outweigh initial costs (Richey et al., 2023), AI-specific CBA adds complexity: benefits often involve knowledge-work augmentation rather than direct labour substitution, and risks such as unreliable outputs or cost overruns must be factored in (Carreno, 2025).

2.3 Administrative automation in logistics

Most AI research in supply chain management (SCM) focuses on forecasting, transport optimisation, and production scheduling, leaving the administrative dimension underexplored. Yet tasks such as data capture, report consolidation, compliance documentation, and communication flows are critical to continuity; delays or errors can disrupt material flow and undermine performance (Każmierczak et al., 2025).

Administrative automation uses technologies like workflow systems and AI-enabled assistants to execute repetitive back-office tasks. Unlike physical automation, it targets clerical and knowledge-based functions, entering supplier data, consolidating metrics, and preparing routine reports. These tasks are rule-based, labour-intensive, and error-prone, making them ideal for automation (Daios et al., 2025).

AI extends these capabilities beyond rule execution through classification, anomaly detection, information extraction, and report generation. Industry studies show growing adoption for billing, order processing, and compliance (Daios et al., 2025), illustrating AI's direct applicability to administrative layers.

Despite global progress, this domain remains one of the least empirically examined areas of AI in logistics, especially in South Africa, where labour-intensive processes, infrastructure constraints, and cost pressures heighten the need for scalable solutions. The automotive sector depends heavily on clerical coordination across parts receiving,

warehousing, sequencing, and supply-to-line operations, yet research on AI assistants in these contexts is scarce. This study addresses this gap by focusing on administrative AI in internal logistics.

Feasibility and impact, however, depend on national conditions. The next section examines South Africa's logistics and manufacturing environment, highlighting how economic, infrastructural, and labour factors shape administrative AI adoption.

3. Proposed Conceptual Framework

The framework comprises four interrelated dimensions: *Adoption Determinants*, *Organisational Change Enablers*, *Economic Justification*, and *Governance and Risk Management*, as shown in Figure 1. Each dimension captures a domain of factors that shape whether AI-driven administration automation can be adopted sustainably within internal logistics. These dimensions are analytically distinct but operationally interconnected. *Adoption determinants* describe the behavioural and technical factors that directly influence user acceptance and system performance. *Organisational change enablers* capture the structural and cultural mechanisms required to support transformation. *Economic justification* establishes whether the investment is feasible and strategically warranted. *Governance and risk management* address the safety, reliability, and accountability requirements necessary when administrative processes influence compliance and traceability.

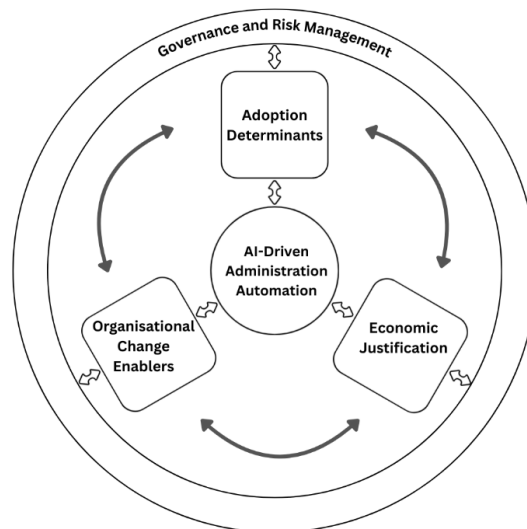


Figure 1. Proposed AI-Driven Administration Automation Conceptual Framework

- Adoption Determinants

This dimension integrates behavioural and technical factors that shape user acceptance and system performance. Drawing on the Technology Acceptance Model (Davis, 1989) and TAM2 (Venkatesh & Davis, 2000), determinants include perceived usefulness, ease of use, job relevance, output quality and result demonstrability. These constructs shape user attitudes towards new systems and influence behavioural intention and actual use.

Technical determinants relate to system integration, data availability, and reliability. Legacy ERP and WMS systems, inconsistent datasets, and interoperability constraints significantly impact whether AI tools can be effectively integrated into daily administrative workflows. Cultural determinants, such as workforce apprehension about job displacement, further shape acceptance and must be addressed to ensure stable adoption.

Perceived usefulness and ease of use reduce the cognitive load associated with repetitive documentation and reporting tasks, while social influence reinforces normative support from peers and supervisors. Without these mechanisms, utilisation becomes inconsistent, constraining efficiency, accuracy, and downstream performance gains.

- Organisational Change Enablers

Adoption of administrative AI requires deeper organisational shifts beyond individual acceptance. Drawing on Lewin's Unfreeze-Change-Refreeze model and contemporary interpretations of Kotter's multi-step change process (Carreno, 2025), this dimension emphasises leadership alignment, clear communication, reskilling, and the development of shared organisational vision.

Internal logistics environments often rely on tacit knowledge and task-specific routines; therefore, shifting to AI-assisted workflows requires structured change management. Enablers include process redesign, stakeholder engagement, creation of pilot environments, and mechanisms for institutionalising new practices. Successful automation thus depends not only on system capability but on the organisation's ability to adapt behaviours, routines, and expectations.

Complementing these perspectives, absorptive capacity and dynamic capabilities (Zahra & George, 2002) explain how organisations acquire, assimilate, transform, and apply new technological knowledge. These capabilities enable organisations to embed AI tools in routine operations and sustain long-term process improvements.

- Economic Justification

Economic justification is essential in environments characterised by tight margins, high logistics costs, and investment uncertainty. Cost-benefit analysis provides a structured basis for evaluating whether administrative automation yields measurable value. Direct benefits include labour savings, reduced processing time, and improved accuracy; indirect benefits include enhanced compliance, better decision quality, and the ability to scale operations. Complementary evaluation tools, including multi-criteria decision analysis, the balanced scorecard (Kaplan & Norton, 1992), and value-based management, extend financial assessments by capturing strategic, non-financial, and compliance-related value. Given resource constraints in internal logistics, investment proposals compete for scarce capital, reinforcing the need for disciplined justification supported by these tools.

- Governance and Risk Management

Before defining this dimension, it must be acknowledged that administrative AI introduces critical categories of risk that were repeatedly emphasised in the literature. Data privacy, cybersecurity, reliability and validation of automated outputs, and regulatory and compliance obligations. A robust governance layer becomes essential for ensuring safe, reliable, and responsible AI deployment. This includes safeguarding data integrity, validating automated outputs, protecting sensitive information, and ensuring alignment with internal and external regulatory requirements.

This dimension draws on established governance frameworks such as ISO (2023), ISO (2022), the European Union Artificial Intelligence Act, and the IEEE Ethically Aligned Design principles (IEEE, 2017). These frameworks establish norms for transparency, accountability, auditability, and data protection, reducing the risk of error propagation and strengthening organisational confidence in AI tools.

4. Methodology

A pragmatic, abductive, mixed-methods design was adopted to capture measurable patterns and practice-based insights across internal logistics functions (parts receiving, warehousing, sequencing, supply-to-line) in a South African automotive manufacturing environment.

Data for the study were generated through two complementary sources: semi-structured interviews and an industry survey. The five semi-structured interviews provided detailed accounts of administrative practices, organisational conditions, and perceptions of AI-driven automation among employees directly involved in parts receiving, warehousing, sequencing, and supply-to-line activities. In parallel, A total of thirty participants completed the survey, representing a diverse mix of operational, supervisory, and managerial roles across the internal logistics environment. Participation in both data-collection activities was voluntary and anonymous, and distribution was facilitated through a neutral organisational gatekeeper to mitigate potential coercion.

Qualitative data were analysed thematically following Braun & Clarke's (2008) six-phase procedure, with codes generated inductively and refined into broader themes. Descriptive statistics of the quantitative data, summarised respondent characteristics, patterns and relationships between determinants of adoption, perceived impacts, and readiness for change.

5. Results

The survey respondents' demographic makeup shows broad coverage across internal logistics roles: 23% are frontline employees, 37% supervisors or team leaders, 20% managers, and 20% fall into other categories like engineers and clerks. This distribution ensures both operational and supervisory viewpoints are included, capturing insights from staff performing administrative duties as well as those supervising them. Respondents had varied levels of experience. 13% had less than one year of experience, 40% had between one and eight years, and 47% had more than eight years in internal logistics. This breadth ensures that the data incorporates both fresh perspectives from newer employees and the institutional knowledge of long-tenured staff.

5.1 Current Administrative Tasks and Perceived Amenability to AI Automation

The findings indicate that administrative work forms a substantial and routine component of internal logistics operations. Survey responses show that most employees perform core administrative tasks daily, with 77% engaged in data capturing, 60% in data consolidation, 67% in report compilation, and 70% in report sharing (Table 2). These activities occupy a considerable proportion of working time, as 30% of employees spend more than three-quarters of their day on administrative work, and another 30% spend between half and three-quarters. The predominance of these tasks echoes observations in the literature, which identify data capture, document processing, and reporting as highly repetitive and rule-based functions well suited to RPA and ML applications.

Table 2. Frequency of core administrative tasks performed

	<i>Data Capturing</i>	<i>Data Consolidation</i>	<i>Report Compilation</i>	<i>Report Sharing</i>
<i>Daily</i>	77%	60%	67%	70%
<i>Weekly</i>	20%	33%	23%	20%
<i>Monthly</i>	0%	3%	10%	7%
<i>Less than Monthly</i>	0%	0%	0%	3%
<i>Never</i>	3%	3%	0%	0%

Interview accounts provide deeper insight into how these tasks are experienced in practice. Participants consistently described their work as dominated by manual and repetitive activities such as capturing attendance, transferring data from SAP or email into Excel, and manually preparing reports.

These qualitative experiences align with the repetitiveness and tediousness reflected in the survey data. Figure 2 and Figure 3 show that participants overwhelmingly perceive administrative tasks as highly repetitive and tedious. Interviewees further identified tasks such as updating KPIs, reconciling stock levels, processing paper-based inputs, and capturing unstructured email content as particularly burdensome. The predominance of Excel as the primary tool, even where digital platforms such as SharePoint Lists or Power BI exist, highlights the persistence of fragmented digital processes and legacy practices.

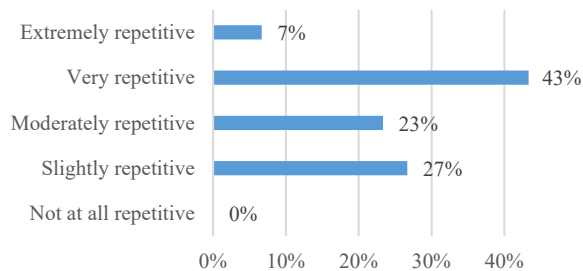


Figure 2. Perceived repetitiveness of administrative tasks among survey participants

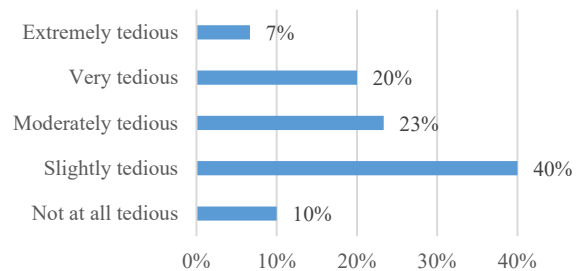


Figure 3. Perceived tediousness of administrative tasks among survey participants

Taken together, the findings confirm that administrative tasks are time-intensive, cognitively unfulfilling, and structurally embedded within outdated or fragmented systems. This combination provides a strong empirical basis for considering AI-enabled automation of rule-based administrative work.

Following this, participants were asked to assess the suitability of various administrative tasks for AI automation. As shown in Table 3, the survey results demonstrate strong support for automation across all activities. Between 70% and 80% of respondents rated each task as very or extremely suitable for automation, and none indicated that AI assistants are not suitable at all. These perceptions were consistent across experience levels and organisational roles, suggesting a broadly shared view regarding the value and feasibility of AI-driven automation.

Table 3. Perceived suitability of AI assistants for automating key administrative tasks among survey participants

	Data Capturing	Data Consolidation	Report Compilation	Trend Identification	Report Sharing
Not suitable at all	0%	0%	0%	0%	0%
Slightly suitable	7%	3%	13%	10%	3%
Moderately suitable	7%	17%	7%	13%	23%
Very suitable	47%	57%	53%	40%	30%
Extremely suitable	40%	23%	27%	37%	43%

Qualitative evidence further explains these perceptions. Three overarching themes emerged from the interviews. Firstly, *automatable reporting and data consolidation*. Participants noted that most reporting and analytical tasks follow predictable, structured workflows governed by fixed rules. Examples include escalating and validating performance reports, processing leave approvals through multiple hierarchical levels and verifying data at each stage. These processes are repetitive and procedurally rigid, making them well-suited to AI tools capable of managing structured data.

Secondly, inventory and data capture, four interviewees highlighted that much of the required information already exists in enterprise systems, suggesting that AI could leverage these datasets to reduce manual data entry and streamline operational tasks. One participant acknowledged that some data capture will remain manual, yet the prevailing view was that AI could support, rather than replace, routine data-intensive tasks.

Thirdly, limits and dependencies of systems and data, participants cautioned that successful automation depends on system integration, clean data inputs, and access to structured databases. Without these foundations, AI risks replicating existing inefficiencies rather than resolving them.

Collectively, the evidence demonstrates strong organisational recognition that rule-based administrative tasks are both burdensome and highly amenable to AI automation, underscoring the strategic potential for AI-driven tools in internal logistics.

5.2 Challenges and Risks of AI Integration

While the preceding section demonstrated strong support for AI-driven automation, the findings also reveal notable concerns regarding the practical challenges and risks associated with integrating AI into administration in internal logistics.

Survey respondents were asked to indicate their level of agreement with statements relating to five areas of concern: data privacy and security, the reliability and accuracy of AI outputs, system integration challenges, potential job displacement, and the difficulty of measuring tangible benefits. Table 4 summarises the results. Employees expressed the highest levels of concern regarding job losses (53% agree or strongly agree), and nearly half (47%) indicated concerns about data privacy and security. By contrast, more than half of respondents remained neutral on issues related to AI reliability (57%) and integration with existing systems (60%), suggesting uncertainty rather than outright apprehension.

Table 4. Perceived risks and challenges associated with AI integration in administrative tasks

	<i>Data privacy & security</i>	<i>Reliability & accuracy</i>	<i>Integration challenges</i>	<i>Job losses</i>	<i>Measurement of benefits</i>
<i>Strongly Disagree</i>	3%	7%	3%	0%	13%
<i>Disagree</i>	10%	13%	13%	3%	40%
<i>Neutral</i>	40%	57%	60%	43%	33%
<i>Agree</i>	43%	17%	20%	23%	13%
<i>Strongly Agree</i>	3%	7%	3%	30%	0%

In contrast, participants in managerial, planning, and engineering roles, who generally spend less time on repetitive administration, expressed considerably lower levels of concern. They perceived AI automation not as a threat but as an opportunity to redirect effort toward higher-value activities, including analysis, optimisation, and strategic decision-making. This divergence underscores the importance of occupational identity and task structure in shaping perceptions of AI-related risk.

The interview results provide further depth to these concerns, revealing three interrelated themes. Firstly, participants highlighted that the effectiveness of AI systems depends heavily on the availability of clean, structured, and reliable data. As one participant noted, *“A lot of data that is generated is not clean enough to be immediately used and needs to be cleaned up before analysis can be done.”* This aligns with literature indicating that fragmented or inconsistent datasets undermine automation accuracy and reliability.

Secondly, participants emphasised the need for training, support, and communication to ensure employees understand how AI systems function, what inputs they require, and how to validate outputs. For example, one participant noted, *“Employees need to understand how the system works so that they can provide feedback on improvements and accuracy.”* Another commented that *“AI courses should be introduced to improve understanding and enable users to engage effectively with the technology.”* These perspectives echo organisational-change theories stressing the importance of communication, capability-building, and leadership alignment.

Thirdly, participants expressed concern that uncritical reliance on AI outputs could introduce errors if results are not rigorously validated. Human oversight, including routine performance monitoring and KPI comparison before and after implementation, was viewed as essential for responsible AI use.

Taken together, these results demonstrate that although employees recognise the potential benefits of AI-driven administrative automation, they remain critically aware of the operational, structural, and ethical complexities that accompany it. Concerns related to job displacement, data privacy, system integration, and workforce readiness highlight the need for deliberate change management, transparent governance, and robust technical preparation. Ultimately, the success of AI in internal logistics will depend not only on the capabilities of the technology itself but also on how effectively organisations prepare their systems, support their employees, and maintain human oversight throughout the automation process.

5.3 Measurement and Quantification of Outcomes

The final component of the results examines how employees believe the success of AI-driven administrative automation should be measured. The findings provide insight into the operational indicators, performance measures, and evaluative criteria employees consider most meaningful in assessing the effectiveness and sustainability of AI automation within internal logistics.

Survey respondents identified a wide range of indicators rather than a single dominant measure, suggesting that employees conceptualise automation success as multidimensional. As illustrated in Figure 4, participants selected metrics relating to efficiency, accuracy, error reduction, information quality, throughput, and decision support. This distribution reflects an understanding that AI performance cannot be captured by productivity measures alone but requires consideration of information reliability, output consistency, and the broader enhancement of administrative processes.

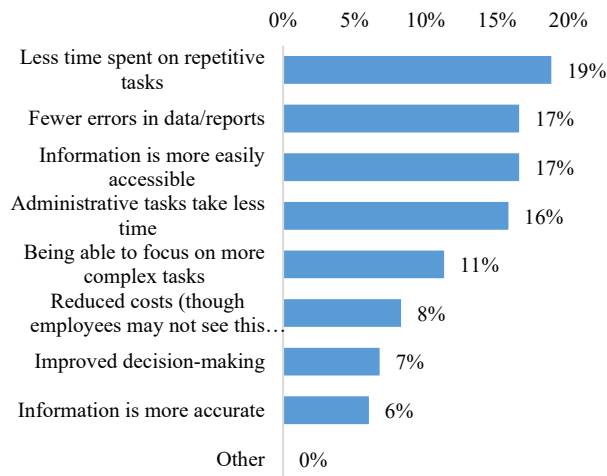


Figure 4. Survey participant perceptions of success indicators for AI-driven administrative automation

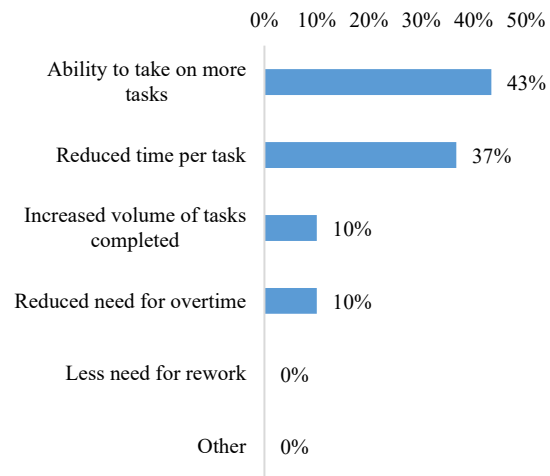


Figure 5. Participant perceptions of metrics for measuring efficiency gains through AI implementation

A complementary question asked respondents how efficiency gains should be measured. As shown in Figure 5, the most frequently selected indicators were the ability to take on more tasks (43%) and reduced time per task (37%). Smaller proportions selected increased task volume and reduced overtime. These preferences indicate that employees perceive efficiency in practical terms, faster task completion, the ability to manage higher workloads, and reduced administrative burden. The limited emphasis on reduced rework suggests that staff prioritise throughput and time savings over quality-related metrics when thinking about efficiency.

Interview findings reinforce this perspective through two interconnected themes. First, reduced administrative time per task was consistently described as the clearest indicator of AI success. Participants associated time savings with improved operational efficiency, reduced administrative costs, and greater availability of capacity for higher-value work. For example, Participant 4 explained that successful automation would be reflected in “*time saved that could be spent on other projects, which can make your business more efficient or improvements in processes.*”

The second theme, throughput and on-time performance, extends beyond individual task speed to encompass broader project timelines and process stability. Participants noted that AI could accelerate administrative cycles, shorten project implementation timeframes, and improve the reliability of scheduled outputs. As Participant 3 observed, automation “*would have an effect on reducing the overall time spent on a particular project, shortening implementation and stabilisation times.*” These insights emphasise that employees evaluate AI success not only through operational speed but also through systemic gains in process predictability and reliability.

Together, these findings indicate that employees conceptualise AI effectiveness as a combination of efficiency, accuracy, consistency, and strategic value. These perspectives support the need for hybrid evaluation frameworks that combine quantifiable metrics (such as time savings, capacity increases, and error reductions) with qualitative assessments of reliability, information usability, and process stability. Overall, employees anticipate that AI will deliver value across multiple dimensions and therefore expect evaluation approaches that capture both labour savings and broader organisational benefits.

6. Discussion

The findings collectively validate the study’s objectives and provide empirical grounding for the proposed conceptual framework. They reveal that successful adoption of AI-driven administrative automation depends on a combination of technical feasibility, organisational readiness, economic viability, and governance safeguards.

First, automation feasibility is strongly associated with task characteristics. Repetitive, rule-based, and data-intensive activities, such as data capturing, consolidation, and reporting, emerged as the most suitable for AI integration. This aligns with the framework’s Adoption Determinants, which emphasise perceived usefulness and ease of use as drivers

of acceptance. However, neutrality regarding reliability and integration signals the need for trust-building measures and robust interoperability.

Second, anticipated performance improvements, including efficiency, accuracy, and time savings, reinforce the importance of Economic Justification. Employees conceptualised success through practical indicators such as reduced task duration and increased capacity, complemented by qualitative benefits like improved decision quality and process stability. These insights underscore the need for hybrid evaluation models that combine operational and strategic metrics.

Third, concerns about job displacement, data integrity, and over-reliance on automation highlight the interdependence of Organisational Change Enablers and Governance and Risk Management. Workforce apprehension and skills gaps point to the need for structured change management, reskilling, and transparent communication. Similarly, data privacy and reliability concerns demand governance safeguards, human-in-the-loop validation, and clear accountability mechanisms.

Building on these insights, the four core dimensions, namely *Adoption Determinants*, *Organisational Change Enablers*, *Economic Justification*, and *Governance and Risk Management*, remain central but require recalibration to reflect operational realities and contextual constraints in South African internal logistics. Table 5 summarises how each dimension was validated, challenged, or expanded by the evidence gathered from surveys and interviews.

Table 5. Dimension, validated, challenged

<i>Framework Dimension</i>	<i>Key Concepts from Proposed Framework</i>	<i>Critical Comparison with Empirical Findings</i>	<i>Refinement Suggestions</i>
<i>Adoption Determinants</i>	Based on TAM and TAM2, emphasising perceived usefulness, ease of use, social influence, and cognitive instrumental processes.	Strong validation: 70–75% agreed that AI improves efficiency, accuracy, and speed. Interviews reinforced suitability for structured, rule-based tasks. Neutrality on reliability (57%) and integration (60%) indicates limited trust and interoperability challenges.	Incorporate sub-factors on user confidence, data integrity, and system interoperability. Introduce iterative testing and user-feedback loops to strengthen trust.
<i>Organisational Change Enablers</i>	Drawn from Lewin and Kotter: leadership, communication, empowerment, reskilling, and reinforcement.	Empirical findings indicated workforce apprehension and skills gaps. 53% feared job displacement; interviewees called for training, clarity, and visible leadership.	Embed ongoing reskilling, psychological safety, phased implementation, and leadership visibility.
<i>Economic Justification</i>	Based on CBA: balancing tangible ROI (time, accuracy, cost) and intangible benefits (decision quality, compliance).	Findings confirmed multidimensional evaluation: 43% prioritised increased task capacity; 37% prioritised reduced time per task. Interviews added consistency, throughput, and decision quality.	Adopt hybrid evaluation models combining operational, financial, and strategic indicators. Include cost-of-quality, error reduction, and iterative ROI tracking.
<i>Governance and Risk Management</i>	Anchored in ISO, IEEE, and EU AI Act principles, ensuring transparency, accountability, privacy, and reliability.	Strong empirical support: data-privacy concerns (47%) and job-security concerns (53%) were the highest risks. Neutrality on reliability suggests limited visibility of governance safeguards. Interviews highlighted the need for human oversight and validation.	Strengthen human-in-the-loop validation, transparent auditing, and ethical workforce-assurance mechanisms. Formalise communication on risks, safeguards, and accountability.

This refinement process ensures that the framework is not only theoretically robust but also practically applicable. For example, Adoption Determinants now incorporate trust-building factors such as iterative testing and user-feedback loops, while Organisational Change Enablers emphasise psychological safety and phased implementation. Economic Justification expands to include hybrid ROI models that capture both tangible and intangible benefits, and Governance and Risk Management strengthens provisions for human oversight, transparent auditing, and ethical workforce assurance.

Drawing on this synthesis, the final framework positions AI-driven administrative automation at the centre, surrounded by four interdependent dimensions that collectively determine feasibility, sustainability, and responsible adoption. Each dimension is dynamically linked, illustrating how technical, organisational, economic, and governance factors interact to shape outcomes. Sub-components such as user confidence, leadership visibility, hybrid ROI indicators, and human oversight operationalise these dimensions, ensuring that theoretical constructs and empirical evidence converge into actionable guidance.

7. Conclusion

This study examined how organisations can implement AI-driven administrative automation in internal logistics and developed an empirically validated framework explaining adoption factors. By integrating survey data and interview insights from operational and managerial perspectives, the research shows that automation is not merely technical but a socio-organisational process shaped by people, procedures, and governance.

Findings reinforce established adoption and change-management theories while extending them through contextual validation. Consistent with TAM and TAM2, perceived usefulness and ease of use were central drivers, though neutrality on reliability and integration highlights sensitivity to data quality and interoperability—underscoring the need for both organisational readiness and robust system design. In line with Lewin’s and Kotter’s models, leadership visibility, transparent communication, and workforce readiness emerged as critical enablers. Concerns about job displacement, particularly among employees with heavy administrative workloads, stress the importance of psychological safety and structured reskilling.

Economic justification proved essential for feasibility. Participants linked success to shorter task durations, increased capacity, and improved accuracy, aligning with cost–benefit principles. Qualitative insights added strategic benefits such as throughput gains, reduced project cycles, and enhanced decision quality. Governance concerns—data privacy, reliability, and job security—reinforce the need for oversight, human-in-the-loop validation, and transparent auditing, consistent with ISO standards, IEEE guidelines, and the EU AI Act. Overall, technological capability, organisational alignment, economic viability, and ethical governance interact to enable sustainable adoption.

The framework advances theory by affirming established constructs and explicitly integrating governance and ethical assurance. Context-specific validation highlights how infrastructural limitations, fragmented systems, and skills gaps shape adoption in emerging economies.

Limitations include single-organisation scope, modest sample size, and reliance on perceptual rather than measured outcomes. Future research should test the framework across multiple organisations, use longitudinal designs to track adoption over time, and incorporate digital-maturity models. Larger-scale quantitative studies could deepen understanding of relationships between adoption determinants, perceived improvements, and operational results.

In conclusion, responsible AI-driven administrative automation depends on the dynamic interplay of technical readiness, organisational capacity, economic justification, and governance safeguards. The proposed framework offers a practical guide for scholars, managers, and policymakers seeking to balance operational gains with workforce assurance and regulatory compliance.

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