Preparing Logistics SMEs for the Adoption of Machine Learning: A Framework for Readiness and Implementation

Aleksandar Stoyanov
Fontys University of Applied Sciences
aleksandar.stoyanov@student.fontys.nl

Frank van der Linden
Logicall
f.vanderlinden@drakeandfarrell.com

Theo de Vries
Greenzone
theodevries@greenzone.nl

Mark Bremen
KLG Europe
m.bremen@venlo.klgeurope.com

Job Vogels
Fontys University of Applied Sciences
j.vogels@fontys.nl

Georgiana Manolache
Fontys University of Applied Sciences
g.manolache@fontys.nl

Abstract

Abcd

Keywords: ML, Logistics, SMEs, Framework, AI Adoption, Organizational Readiness, Digitalization

I. Introduction

Over the past decade, artificial intelligence (AI) has been increasingly adopted across various industries, facilitating advancements in efficiency, innovation, and competitiveness. The European Commission seeks to achieve the digitalization of seventy-five percent of businesses by 2030 through the adoption of AI, cloud computing, and big data. As part of the strategy, ninety percent of small and medium-sized enterprises (SMEs) are expected to attain at least a fundamental level of digital intensity [1]. SMEs occupy a pivotal position in the transition, not only because they constitute the majority of companies in the European Union but also because they serve as a critical source of innovation [2].

Advancements in technology have significantly improved SMEs' efficiency across industries through the application of various techniques [3]. These include AI-driven solutions, such as System Applications and Products in Data Processing (SAP) Integrated Business Planning [4], which optimize demand forecasting, inventory control and reduce costs [5]; cloud computing and enterprise resource planning (ERP) systems, such as Oracle NetSuite [6], which streamline business operations and improve decision-making [7, 8]; blockchain-based solutions, such as VeChainThor [9], that improve transparency and security in commercial transactions [8, 10]; cyber security measures, such as Microsoft Azure Active Directory [11], ensuring data integrity [12, 13]; and e-commerce digital marketing tools, such as Shopify [14], which expand market reach, enhance customer engagement, and increase revenue while minimizing operational costs [15].

Among the sectors undergoing digital transformation in accordance with the European Commission strategy, logistics companies play a vital role in ensuring supply chain efficiency and commercial operations [1, 16]. As digitalization accelerates, these enterprises increasingly rely on advanced technologies to optimize processes, reduce costs, and enhance operational resilience [17]. However, logistics SMEs encounter great difficulties in adapting to digitalization compared to larger enterprises due to limited financial resources, technological infrastructure, and specialized expertise [18, 19]. These factors hinder the effective preparation and integration of digital solutions, limiting the competitiveness and scalability of logistics SMEs. Machine learning (ML) represents a viable technological solution for logistics SMEs, as its implementation requires relatively minimal financial investment, infrastructure, and specialized expertise while offering significant potential for process optimization and operational efficiency [20, 21] .

The study proposes a framework designed to prepare logistics SMEs for the adoption of ML techniques. Three real-world processes, representative of common practices within such organizations, serve as case studies to evaluate the framework's applicability. The framework addresses technological, organizational, and regulatory readiness to facilitate effective integration of ML solutions.

The contribution of the paper can be seen in:

- A ML readiness assessment framework that enables logistics SMEs to evaluate their preparedness for adoption across technological, organizational, and regulatory dimensions.
- A ML preparation framework designed to support logistics SMEs in achieving readiness for ML adoption.

The remainder of the paper is structured as follows. Section 2 examines the background research essential for understanding contextual information about logistics SMEs and ML. Section 3 reviews related work in comparable fields and use cases. Section 4 outlines the methodologies employed to conduct the experiment.

Section 5 presents the results of the experiment, while Section 6 applies these findings to real-world case studies. Section 7 addresses the limitations of the study. Section 8 provides a discussion of the findings. Section 9 concludes the paper. Section 11 contains supplementary material that substantiates the findings of the paper and opens with a glossary.

II. Background Research

A) Small and Medium-Sized Enterprises

Small and medium-sized enterprises (SMEs) play a vital role in economic growth, innovation, and employment. However, defining SMEs remains inconsistent across institutional and academic frameworks. Table 1 showcases how the European Commission classifies SMEs as enterprises with fewer than 250 employees and an annual turnover not exceeding fifty million euros [22], ensuring regulatory uniformity across member states.

SMEs constitute over 95% of global businesses, employing approximately 60% of the workforce and generating nearly 40% of GDP [23, 24]. Within the European Union, they provide two-thirds of private-sector employment and contribute significantly to gross value added [25]. Despite their economic significance, SMEs face persistent challenges, including limited financial access, regulatory burdens, and technological adaptation constraints [26].

The ability to adopt emerging technologies, including artificial intelligence and digital commerce, remains crucial for SME competitiveness. However, many lack the necessary infrastructure and expertise, widening the gap between small enterprises and large corporations [27]. Effective knowledge management further influences long-term sustainability, yet many SMEs rely on informal learning mechanisms rather than structured knowledge retention strategies. This reliance increases vulnerability to knowledge loss, particularly when key personnel exit the organization [28, 29]. Given these constraints, targeted policies that support financial access, digitalization, and organizational learning are essential to strengthening SME resilience and growth [30, 31].

B) Logistics Companies

Logistics companies facilitate the movement of goods, information, and resources through transportation networks and distribution systems, ensuring supply chain efficiency and timely deliveries [32, 33]. Their operations are structured around spatial networks, with headquarters typically located in urban centers and distribution facilities situated in suburban areas. Logistics management encompasses transportation, warehousing, and inventory control, with logisticians responsible for coordinating these activities to minimize costs and improve resource allocation [34].

Logistics enterprises are classified according to their role within the supply chain, including freight carriers, warehousing and distribution providers, supply chain management firms, freight forwarders, third-party logistics (3PL) providers, fourth-party logistics (4PL) providers, and integrators, as detailed in Table 2.

Table 1 | European Commission SME Definition [22]

Company Category	Staff Headcount	Turnover	Balance Sheet Total
Medium-Sized	< 250	≤ € 50 m	≤ € 43 m
Small	< 50	≤ € 10 m	≤ € 10 m
Micro	< 10	≤ € 2 m	≤ € 2 m

Table 2 | Types of Logistics Companies and their Function

Type	Function
Freight Carriers [35]	Transport goods across multiple modes, including road, rail, sea, and air. Road carriers handle short to medium distances, rail carriers transport bulk freight, sea carriers facilitate international trade, and air carriers ensure expedited delivery of high-value shipments.
Warehouse and Distribution Providers [36]	Store goods and manage their movement to final destinations. Warehousing includes inventory management and security, while distribution providers handle order fulfillment and ensure timely deliveries.
Supply Chain Management Firms [37]	Oversee entire supply chains, from procurement to final delivery. Their focus is on optimizing logistics operations, reducing costs, and implementing strategic planning.
Freight Forwarders [35]	Act as intermediaries between shippers and carriers. They coordinate shipments, manage regulatory documentation, and simplify complex international trade logistics.

The increasing digitalization of logistics operations, including the implementation of logistics management software and the Internet of Things (IoT), plays a fundamental role in streamlining processes and facilitating outsourcing decisions. These decisions are primarily influenced by considerations related to cost efficiency, risk management, and operational control [38]. Logistics companies have increasingly adopted advanced digital solutions such as real-time tracking systems, automated warehouse management systems, and predictive analytics to enhance operational efficiency. For instance, digital twins (virtual representations of physical supply chain systems) are employed by companies such as DHL to simulate logistics scenarios and optimize decision-making [39]. Similarly, blockchain technology has been integrated into supply chain management by firms like Maersk to enhance transparency and security in global trade operations [40]. Despite these advancements, the industry faces significant challenges, including capacity constraints, infrastructure congestion, and evolving regulatory requirements, particularly in ports and transportation networks, which contribute to increased operational costs and delivery delays [41].

The imposition of stricter safety and environmental regulations, such as carbon reduction initiatives under the European Union's Clean Industrial Deal, further necessitates substantial investment in sustainability measures [42]. In response, AI-driven solutions have emerged as a viable means of addressing these challenges. Machine learning algorithms are increasingly used for demand forecasting, optimizing fleet routing, and reducing fuel consumption. For example, UPS has implemented AI-based route optimization software (ORION) to minimize unnecessary mileage and emissions, while Amazon utilizes AI-powered robotics in its warehouses to streamline order fulfillment [43, 44]. As digital transformation continues to reshape logistics operations, the integration of AI-based solutions presents significant opportunities for enhancing efficiency, resilience, and sustainability across the sector.

For information on how logistics companies cope with the challenges they face, refer to **section Appendices – Challenges in Logistics**.

C) Machine learning, Readiness, and Frameworks

ML, a subset of AI, involves the development of algorithms that enable systems to learn from data, recognize patterns, and make predictions without explicit programming [45]. This capability allows computers to continuously improve performance by analyzing information autonomously. ML has broad applications across natural language processing, computer vision, speech recognition, and predictive analytics. In predictive analytics, ML identifies trends and behaviors, offering valuable insights for industries such as healthcare, finance, and logistics [46, 47].

For further information on the application of machine learning in logistics, as well as an extended discussion of its associated privacy, security, and ethical considerations, refer to **section Appendices - ML in Logistics** and **Privacy, Security, and Ethical Considerations**, respectively.

Table 3 and Table 4 illustrate a snippet of a multi-criteria decision matrix which compares different ML methods, algorithms, and paradigms on multiple aspects. The selection of comparison criteria for evaluating machine learning methods in Table 3 is guided by an extensive review of academic literature and established evaluation frameworks in applied ML research [48, 49, 50, 51, 52, 53]. The criteria are chosen to reflect a comprehensive and balanced perspective, incorporating both technical performance and practical applicability.

The criteria of performance and accuracy serves as a benchmark for empirical reliability by indicating a model's capacity to learn from and generalize to unseen data. Assessing efficiency and computational complexity is critical for deployment in environments with limited computational capacity. Data dependency and sample efficiency are particularly relevant as many logistics SMEs possess limited or incomplete datasets, making sample-efficient models more suitable for implementation. Interpretability and explainability are vital for stakeholder acceptance and operational trust, enabling non-expert users to understand and act on model outputs. Adaptability and transferability support the application of trained models across varying operational contexts, such as different warehouses, routes, or product categories. Ethical considerations and bias mitigation examine how models address fairness and inclusivity. This category acknowledges the societal impact of algorithmic decisions and evaluates mechanisms for reducing discriminatory outcomes. Cost and implementation feasibility are fundamental for SMEs, which often operate under strict budgetary and technical constraints, making accessible and deployable models a necessity. Resilience to adversarial attacks safeguards sensitive logistics operations against manipulation or disruption, thereby preserving system integrity and business continuity.

In addition to the technical evaluation, a separate set of comparison criteria is developed in Table 4 to assess the suitability of ML methods from the perspective of logistics-focused SMEs. These criteria are derived from the most frequently cited concerns from logistics SMEs' representatives, identified through survey responses and qualitative insights obtained during interviews.

Time-Series Forecasting, Online Learning, and Reinforcement Learning emerge as the most suitable approaches due to their adaptability, computational feasibility, and alignment with logistics SMEs' operational demands. These methods provide a balance between predictive accuracy, efficiency, and scalability, enabling AI-driven improvements in supply chain management. Time-Series Forecasting enhances demand prediction by leveraging historical trends, ensuring optimized inventory planning and minimizing stock shortages. Online Learning supports spare parts management by continuously updating models with real-time data, allowing logistics SMEs to adjust procurement strategies dynamically while reducing retraining costs. Reinforcement Learning optimizes subcontractor allocation and shipment combination by continuously learning from historical performance, cost efficiency, service reliability, and capacity availability. As an additional outcome of the multi-criteria decision matrix, the remaining investigated methods, along with further analysis of the aforementioned approaches, are presented in **section Appendices – Additional ML Information**.

Table 3 | Technical Evaluation of ML Methods

ML / Criteria	Performance and Accuracy	Efficiency and Computational Complexity	Data Dependency and Sample Efficiency	Interpretability and Explainability	Adaptability and Transferability	Ethical Considerations and Bias Mitigation	Cost and Implementation Feasibility	Resilience to Adversarial Attacks
Time-Series Forecasting [56]	High performance in temporal pattern prediction with sufficient historical data, ensuring reliable demand forecasting.	Efficient for structured time-series data but computationally intensive for large datasets and deep learning models.	Heavily reliant on extensive historical data, with performance degrading when time-series continuity is disrupted.	High interpretability in traditional models like ARIMA, but reduced explainability in deep learning approaches such as LSTMs and transformers.	Limited adaptability to new datasets, with low transferability across domains, often requiring retraining for different time-series applications.	Less prone to societal biases but can reinforce historical data biases, potentially leading to inaccurate or unfair forecasting outcomes.	Implementation costs vary depending on data preprocessing and model complexity, with higher costs for deep learning-based forecasting.	Vulnerable to adversarial manipulation, as small perturbations in historical data can significantly impact future predictions.
Online Learning [51]	Accuracy depends on data stream quality and often requires adaptive algorithms to ensure consistency.	Efficient for real-time processing but depends on adaptive algorithms to handle complexity.	Efficiency relies on a continuous stream of high-quality data, but concept drift can diminish effectiveness over time.	Interpretability varies by algorithm, with adaptive models favoring performance over explainability.	Highly adaptive to dynamic environments but vulnerable to concept drift if data distribution changes are not properly managed.	Prone to bias if real-time data streams reinforce societal inequalities or propagate misinformation.	Cost-effective for continuous data streams but increases when adapting to concept drift.	Vulnerable to concept drift and adversarial influences in data streams.
Reinforce-ment Learning [52]	High accuracy in dynamic environments but reliant on reward design and exploration strategies.	Computationally demanding due to iterative exploration and reward optimization.	Requires extensive environmental interaction for learning, with low sample efficiency due to its trial-and-error approach.	Decision-making is difficult to explain due to complex reward structures and policy learning.	Highly adaptive in familiar settings but struggles with transferability unless reward functions and policies are aligned.	Biases can arise from reward structures, leading to ethically problematic behaviors if objectives are misaligned.	High implementation costs due to computational demands and environment simulation requirements.	Vulnerable to adversarial policies that exploit reward functions.

Table 4 | Non-IT SME Important Factors Evaluation on ML Methods

ML / Criteria	Ease of Implementation and Integration	Data Availability and Quality	Transparency	Operational Impact and Workflow Integration	Support and Maintenance	Risk Management and Data Privacy	Scalability and Futureproofing	User-Friendliness and Training Requirements
Time-Series Forecasting [56]	Easily deployable for structured time-series data, but deep learning models require specialized expertise.	Highly dependent on extensive historical data, with performance declining when data is sparse or inconsistent.	Traditional models like ARIMA offer clear insights, but deep learning-based forecasting remains a black-box approach.	Seamlessly enhances demand forecasting and inventory planning but requires periodic model retraining for accuracy.	Needs continuous monitoring and updates, particularly in volatile markets where trends shift rapidly.	Sensitive to data privacy concerns, requiring robust encryption and access control for compliance.	Scales well with structured data, but deep learning models demand high computational resources for large-scale forecasting.	Traditional models are easy to interpret, but deep learning-based approaches require domain expertise and specialized training.
Online Learning [51]	Easy to integrate into real-time systems, though continuous adaptation complicates implementation when data quality fluctuates.	Continuous data availability remains essential. Model performance declines with noisy or outdated data streams.	Moderate transparency, though continuous adaptation complicates interpretation.	Moderate impact due to continuous model updates. Workflow integration requires real-time data pipelines and adaptive system designs.	Continuous maintenance required to manage real-time data streams and address concept drift.	High privacy risks due to continuous data processing. Risk management requires real-time monitoring and anomaly detection.	High scalability for real-time data streams, though concept drift increases resource demands.	Moderate user-friendliness, though real-time adaptation complicates deployment.
Reinforce-ment Learning [52]	Complex to implement due to iterative learning and environment simulations, but highly effective for optimizing dynamic decision-making processes.	Highly dependent on extensive interaction with the environment, with data quality reliant on accurate simulations and feedback loops.	Poor transparency due to complex policy learning and unpredictable environment interactions.	High operational impact, requiring infrastructure capable of real-time adaptation and continuous interaction with dynamic environments.	Demands frequent updates and policy refinements to maintain accuracy as environments evolve.	Moderate privacy risks when sensitive data is used in reward functions, but well-defined policies enhance security and regulatory compliance.	Highly scalable when trained on generalized policies, but performance depends on computational resources and adaptation to new environments.	Requires expertise in environment modeling and reward optimization, but once deployed, automates complex decision-making with minimal human intervention.

III. Related Work

A) Existing AI Assessment Readiness Frameworks

In the context of addressing operational challenges within the logistics industry, the adoption of ML necessitates a structured approach to ensure effective implementation. Machine Learning Readiness Frameworks and Methodologies provide systematic guidelines to assess and enhance an organization's preparedness for integrating ML technologies.

Two frameworks are particularly notable for their exclusive focus on SMEs, offering insights directly aligned with this study's objectives. The **AI Guidelines and Ethical Readiness Inside SMEs framework** [56] synthesizes literature and industry guidelines to identify actionable recommendations for fostering responsible AI adoption within SMEs. It advocates for sector-specific ethical standards, accreditation mechanisms, targeted training in AI ethics, and greater awareness of explainable AI and risk-based assessments - elements that reinforce this study's emphasis on transparency. Complementing this perspective, the **AI Readiness Assessment in Malaysian SMEs framework** [57] proposes a conceptual model grounded in human capital, process optimization, and infrastructural readiness. By highlighting the interconnectedness of resource constraints, knowledge gaps, and technological uptake, it provides a useful template for assessing ML feasibility in non-technical business environments. Furthermore, its alignment with national policy objectives underscores the importance of embedding strategic priorities and compliance to regional laws into readiness evaluation frameworks.

Several frameworks emphasize the technical, infrastructural, and lifecycle dimensions of ML readiness. The **AI Data Readiness Inspector (AIDRIN)** [58] offers a quantitative approach to evaluating data suitability for AI applications, addressing both conventional data quality issues and AI-specific metrics such as fairness and class imbalance. Its systematic treatment of data readiness presents a replicable methodology for ensuring the foundational integrity of ML systems, particularly useful for this study's focus on data-dependent models. The **Cisco AI Readiness Index** [59] extends this technical lens by benchmarking readiness across six weighted pillars, providing a stratified view of organizational preparedness that can be translated to resource-constrained environments, such as SMEs. Similarly, the **Technology Readiness Levels for Machine Learning (MLTRL) framework** [60] introduces a structured systems engineering protocol, enabling rigorous evaluation of ML systems through defined developmental stages and risk checkpoints. Its emphasis on lifecycle evaluation and robust safeguards aligns with this study's objective of ensuring stable and responsible ML adoption in non-technical domains. Finally, the **Five Maturity Levels of Managing AI framework** [61] provides a staged framework for assessing enterprise-level AI integration, offering insights into the evolving organizational commitment and capability across maturity phases.

Other frameworks focus more explicitly on organizational, strategic, and socio-technical readiness. Holmström's **AI Readiness Framework** [62] situates AI within digital transformation, evaluating readiness through dimensions such as technologies, activities, boundaries, and organizational goals. Its inclusion of organizational goals as a readiness factor offers practical guidance for aligning ML use cases with firm-level strategic objectives. The **Organizational Readiness for AI Adoption model** [63] emphasizes internal change capacity, including leadership, innovation culture, and infrastructural maturity. Aligned with this perspective, the **Readiness Model for Artificial Intelligence in Business Enterprises** [64] proposes a multidimensional structure encompassing governance, employee culture, and strategic alignment. These multifactorial approaches provide this study with a comprehensive checklist to assess organizational conditions preceding ML implementation. Lastly, the UAE-based framework **Assessing AI Readiness Across Organizations** [65] combines the Technology-Organization-Environment (TOE) [66] and Diffusion of Innovation (DOI) [67] theories, proposing a socio-technical readiness structure that integrates contextual factors such as national policy, sectoral priorities, and local implementation barriers. This alignment with local contextual factors supports the idea that ML readiness assessments should be customized, a notion echoed throughout this study.

Existing machine learning readiness frameworks provide valuable foundations but remain largely generic, offering limited relevance for logistics-specific SMEs. They neglect the operational realities of the logistics sector, such as supply chain interdependencies and fragmented infrastructure. Moreover, while many frameworks assess AI readiness at a general organizational level, they do not explicitly address the distinct challenges associated with ML technologies, including data dependency, model variability, and iterative development. Additionally, current frameworks insufficiently address key concerns surrounding data privacy, cybersecurity, and ethical risks - factors particularly salient given the sensitive nature of logistics data. This study addresses these gaps by developing a tailored readiness assessment framework grounded in the logistical context and informed by empirical SME insights.

B) Existing ML / AI Preparation Frameworks

Existing ML Preparation Frameworks offer structured, scalable approaches for non-IT logistics SMEs, guiding them through AI adoption while aligning solutions with business objectives and operational realities. By leveraging phased implementation, capacity building, and continuous evaluation, logistics SMEs can successfully integrate AI-driven solutions into supply chain operations, enhancing efficiency, resilience, and service delivery. Figure 1 illustrates the key strategies derived from these frameworks for successful AI adoption.

Two frameworks stand out for their explicit focus on ML adoption within SMEs, offering insights directly aligned with the objectives of this study. The **ML Implementation in SMEs framework** [68] is grounded in a quantitative study across multiple industries, identifying key organizational conditions that influence ML uptake, such as data quality, managerial support, and investment readiness. It highlights that successful ML integration in SMEs depends not only on technical feasibility but also on internal preparedness and strategic intent. This focus on real-world constraints offers valuable input for designing a readiness model rooted in practical logistics-sector realities. The **Chameleon Framework** [60], in turn, proposes a semi-automated ML system tailored to the limited resources of SMEs. It simplifies ML development through modular components that support data preprocessing, model selection, training, and deployment, reducing the need for in-house technical expertise. Its automation logic and lightweight architecture serve as an operational model for adapting ML technologies to environments with constrained capacity and domain-specific requirements, such as those found in logistics SMEs.

Several other frameworks explore AI adoption more broadly within SMEs, focusing on strategic alignment and staged preparation. The **AI Adoption by SMEs to Achieve Sustainable Business Performance framework** [70] applies the TOE model to identify contextual drivers of adoption, such as perceived advantage and regulatory pressure. It offers a sustainability-oriented perspective that aligns well with long-term implementation planning in logistics. The **Strategic AI Adoption in SMEs framework** [62] proposes a prescriptive, five-phase model (ranging from awareness-building to the development of task-specific AI

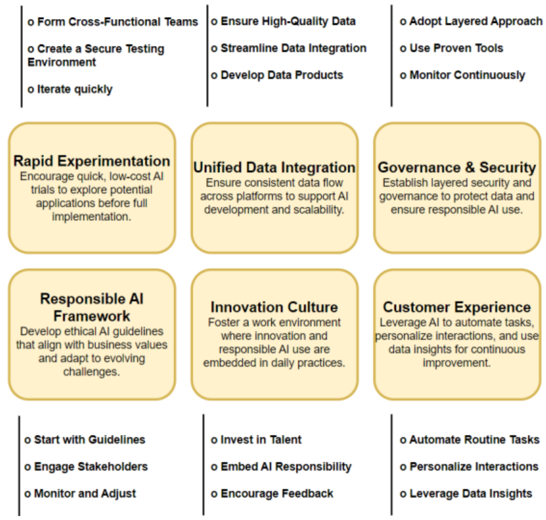

Figure 1 | Potential strategies for SMEs to focus on while preparing for adopting ML / AI

tools) intended to overcome common barriers such as cost and resistance. This staged approach informs the sequencing logic of readiness evaluation in logistics SMEs. Lastly, **The New Normal framework** [72] provides a systematic literature review of 106 studies, classifying barriers and enablers of AI adoption into eight categories. Its holistic categorization enables this study to benchmark and refine sector-specific readiness indicators through an evidence-based lens.

A smaller group of frameworks addresses AI preparation at the enterprise level, offering structurally mature but resource-intensive models. **Building Blocks of an AI Framework for an Enterprise** [73] outlines a six-layer architecture with emphasis on data integration, AI asset modularity, and system interoperability. It provides a technical blueprint for scalable AI deployment, from which modular thinking and platform flexibility can be abstracted and translated to the SME context. The **Corporate Artificial Intelligence Strategy** [74] focuses on aligning AI efforts with digital transformation initiatives and enterprise-wide strategic objectives. Its emphasis on governance and infrastructure modernization offers guidance for structuring long-term capability planning. Finally, the **Rising with the Machines framework** [75] introduces a sociotechnical framework grounded in organizational socialization theory, advocating for the co-adaptation of employees and AI systems. Its attention to human-AI collaboration informs this study's ethical and operational considerations, particularly in logistics settings where human oversight remains critical.

Existing AI preparation frameworks frequently prioritize strategic transformation objectives, yet they often fail to account for the procedural and operational foundations necessary to initiate ML adoption in SMEs. They provide limited guidance for navigating the transition from exploratory interest to initial technical experimentation - a phase that is particularly critical for logistics SMEs with limited prior engagement in data-driven innovation. Furthermore, the lack of diagnostic mechanisms for identifying functional discrepancies between current capabilities and ML requirements further restricts their applicability. Moreover, few frameworks advocate for modular or pilot-based implementation strategies that mitigate adoption risks - an essential consideration for SMEs operating under significant financial and operational constraints. This study addresses these deficiencies by introducing a logistics-oriented preparation framework that structures ML adoption as a sequence of context-specific, actionable steps grounded in sectoral realities.

IV. Methodology

A) Problem Definition

Despite the strategic emphasis placed by the European Commission on accelerating digitalization among SMEs, logistics SMEs continue to experience considerable challenges in preparing for and adopting ML solutions. These challenges primarily originate from structural limitations in financial resources, digital infrastructure, and human capital, which collectively hinder the systematic development of organizational readiness.

Although ML technologies are increasingly recognized for their capacity to improve operational efficiency with relatively low initial investment, the absence of a structured and context-specific preparation framework impedes logistics SMEs from identifying and addressing the prerequisites necessary for successful ML integration. Moreover, current AI preparation frameworks lack the granularity required to reflect the distinct technological, organizational, and regulatory constraints specific to the logistics sector. Consequently, a practical and theoretically grounded preparation and readiness framework tailored to the operational realities of logistics SMEs is required to bridge the gap and enable informed, strategic progression toward ML adoption.

B) Surveys

A series of structured surveys are administered to both decision-makers and operational staff within the participating logistics SMEs. A total of nine individuals completed the surveys, comprising three respondents from each participating SME. The structure consists of sixteen questions, structured into five thematic sections: Demographic and Organizational Background, Current Operational Processes, Process-Specific Challenges and Objectives, Awareness of and Willingness to Adopt Technological Solutions, and Final Open-Ended Reflections.

The decision to employ open-ended or closed-ended formats is based on the nature and depth of information sought in each section. Open-ended questions are used to elicit detailed, context-specific insights into operational processes and perceived inefficiencies, whereas closed-ended formats are applied where categorical or binary responses are sufficient for comparative and statistical analysis.

The data collection instruments serve a dual purpose. First, they enable the identification of case-specific processes within each organization that may benefit from the application of the proposed framework and the subsequent integration of ML techniques. Second, the surveys aim to detect cross-organizational patterns by eliciting information concerning commonly encountered operational challenges, decision-making practices, and perceived barriers to ML adoption. Particular attention is directed toward uncovering recurring obstacles such as an overreliance on intuition-based decision-making, and management of large data volumes, which are observed to impede process efficiency. Additionally, several key inhibitors of ML implementation are identified, including limited financial capacity, a perceived incongruity between ML solutions and core business objectives, and a shortage of internal expertise necessary for operating advanced IT systems. The surveys also explore prior experiences with technological adoption and the principal concerns expressed by SMEs regarding such transformations, as shown in Figure 2.

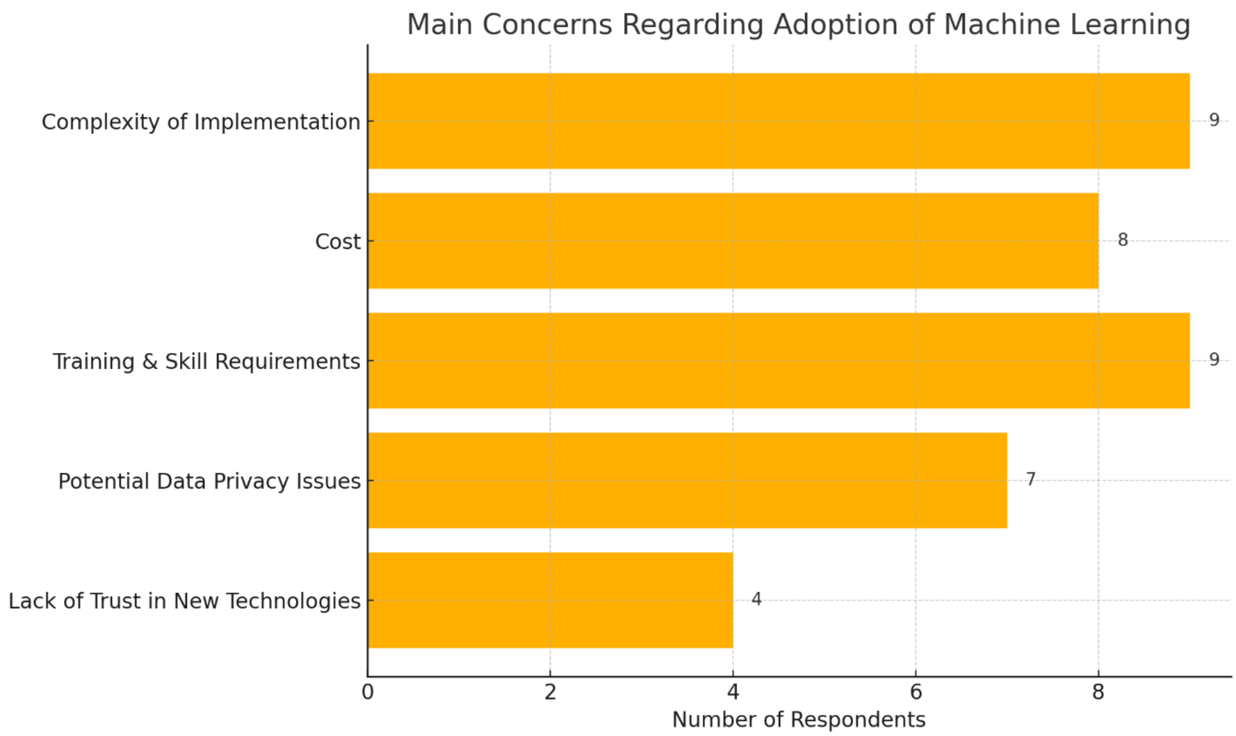

Figure 2 | Survey Responses Regarding Concerns of ML Adoption

Beyond these diagnostic objectives, the survey responses also facilitate the visualization of both the current and desired states of core processes within the participating SMEs that serve as case studies for the application of the proposed frameworks. Furthermore, the results provide valuable insight into the expected level of technological proficiency among the target group, revealing a widespread lack of familiarity with digital tools.

To consult the complete structure and full list of survey questions, refer to **section Appendices – Survey Structure**.

C) Interviews

Interviews are conducted with both representatives of the participating logistics SMEs and specialists in the field of ML. Following the analysis of survey results, SME representatives are interviewed to further explore processes lacking ML integration and to identify areas of interest for potential application. For instance, one SME representative highlighted the company's reliance on manual inventory tracking systems, noting frequent stock discrepancies and delays in order fulfillment. This process, currently devoid of ML integration, is identified as a key candidate for predictive inventory optimization through demand forecasting algorithms. These discussions provide a more detailed understanding of operational shortcomings and inform the refinement of frameworks.

Moreover, they further investigate the concerns and potential challenges associated with the adoption of ML within organizational processes. During the interviews, several participants expressed apprehension regarding the complexity of integrating ML into existing workflows. One respondent noted that while management showed interest in automation, there was significant internal resistance due to limited technical expertise and concerns about data privacy compliance under current regulatory standards. Another objective of the interviews is their integration during the framework development phase. The insights obtained, in conjunction with a comprehensive literature review on best practices in comparable frameworks, facilitated the design of categories and concepts, specifically tailored to the operational context and constraints of logistics-focused SMEs. They provided deeper insight into the distinctions among the participating logistics SMEs, thereby supporting the classification of varying levels of readiness across the defined framework categories, as well as the foundation for establishing and prioritizing requirements regarding the proposed framework.

Subsequently, once the ML Readiness Assessment Framework has been developed, additional interviews are held to evaluate the level of readiness across the three participating SMEs based on the newly defined readiness categories. For example, an SME manager was asked to assess their organization's current digital infrastructure in relation to the framework’s categorization. The participant identified gaps in data centralization and workforce technical training, placing the firm in a preliminary readiness stage.

The insights gained during the phase contribute to the adaptation of the framework to ensure its applicability within the constraints of available SME resources. Further input is used to tailor the framework to the specific characteristics of logistics operations, enhancing its practical relevance. Interviews are also employed to validate key elements of the framework, focusing on perceived feasibility, implementation difficulty, and alignment with strategic objectives. During validation, a respondent expressed concerns regarding the integration of ML models without disrupting existing enterprise software systems. This concern supported the classification system and IT maturity as a core evaluation criterion in the framework.

In parallel, interviews are held with AI specialists to incorporate domain-specific expertise into the design of the framework. Their input supports the development of a modular, progressive implementation structure and informs the definition of distinct technical levels, each representing a different stage of ML readiness applicable to SMEs.

For an overview of the interview structure used during the framework development phase, refer to **section Appendices – Interview Structure**. For the output of prioritized requirements derived from the interviews, refer to **section Appendices – Prioritized Requirements**.

D) Assessment Procedure and Scoring Model

To evaluate the extent to which logistics-oriented SMEs are prepared to implement ML technologies, a two-tiered assessment procedure is developed. The approach integrates both a binary qualification condition and a continuous scoring mechanism. The purpose of the structure is to differentiate between minimum readiness compliance and overall maturity across the assessment framework.

The framework itself comprises eight core categories, each of which encapsulates five individual readiness concepts. Each concept is evaluated on a five-level ordinal scale, ranging from Level 1 (no awareness) to Level 5 (optimized integration). These levels represent progressively advanced stages of organizational development with regard to ML readiness. Within each category, the overall category score is computed as the minimum of the five concept scores, thereby ensuring that no individual area within the category falls below the claimed level of maturity.

Formally, for any given category c_i containing five concepts evaluated as $L_{i1}, L_{i2}, \ldots, L_{i5} \in \{1, 2, 3, 4, 5\}$, the category readiness score R_i is defined as:

$$R_i = \min\{L_{i1}, L_{i2}, L_{i3}, L_{i4}, L_{i5}\}$$

The conservative computation guarantees that high performance in select concepts cannot compensate for a lack of foundational readiness in others within the same category.

Minimum Qualification Criterion

A firm is considered ML ready if it satisfies the following condition:

$$ML\ Ready \leftrightarrow R_k \geq 4 \wedge R_i \geq 3\ \forall i \neq k$$

where k is the index corresponding to the Data Readiness category. The criterion establishes that an organization must attain a minimum of Level 3 across all categories, while Data Readiness must be at Level 4 or higher due to its foundational role in the success of ML implementations.

Normalized ML Readiness Score (NMRS)

In addition to the binary qualification condition, a continuous readiness index is formulated to capture an SME's relative maturity across the entire framework. The NMRS provides a value between zero and one and is defined as follows:

$$NMRS = \frac{1}{8}\sum_{i=1}^{8}\frac{R_i - 1}{4}$$

The formula first transforms each category readiness score $R_i \in [0,1]$, then computes the arithmetic mean across all eight categories, assuming equal weights. The transformation ensures comparability across categories and allows benchmarking over time or across SMEs.

An NMRS value of 1 indicates full optimization across all assessment dimensions, whereas a score of 0 indicates complete lack of readiness. Although an NMRS of 0.625 numerically corresponds to the scenario in which all categories achieve their respective minimum thresholds for ML readiness, this index is not intended as a qualification mechanism; rather, it serves to illustrate the degree of developmental progress across categories and to support targeted capacity-building interventions.

E) Normalization of Readiness Indexes Across Frameworks

aasd

F) Case Studies

To illustrate the practical applicability of the ML Preparation & Readiness Assessment Framework, three real-life case studies are employed. Each case study represents a distinct operational process derived from one of the participating logistics SMEs that demonstrates clear potential for improvement through the adoption of ML. The framework's guidance is applied to each case where relevant, within a controlled and simulated environment. This includes, but is not limited to, processes such as data enrichment, strategic alignment evaluation, and preliminary readiness assessment. The objective of these case studies is to validate the framework's relevance, adaptability, and capacity to support SMEs in identifying actionable pathways toward ML integration.

V. Results

A) ML Preparation & Readiness Assessment SME Framework

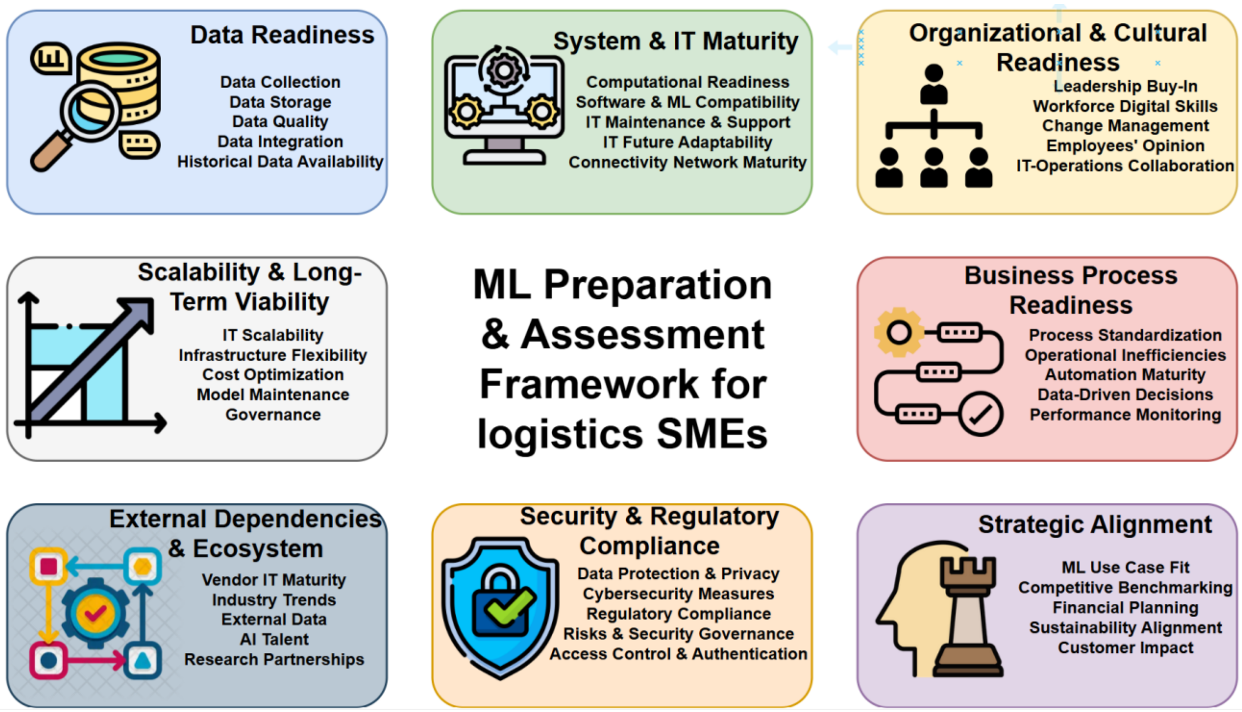

Figure 3 | Visual Representation of Categories and their Concepts in the ML Preparation & Readiness Assessment Framework

Figure 3 provides a visual representation of the proposed categories and associated concepts within the ML Preparation and Readiness Assessment Framework. The framework consists of eight categories, each comprising five concepts, designed to assess the readiness and preparation levels of logistics-oriented SMEs for ML adoption, which are further described in Tables 5 – 12. It further offers targeted guidance to support these enterprises in leveraging the full potential of ML. Each category is accompanied by a dedicated readiness matrix, and guidance is tailored according to the readiness index achieved across the respective concepts. Category-level guidance is presented, while detailed concept-specific guidance, including the purpose and practical considerations for each recommendation, is provided in **section Appendices – Detailed Guidance**.

Table 5 | Data Readiness Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
Data Collection	Logistics data is often written down or typed manually (e.g., paper forms, spreadsheets),	Data is entered into basic digital tools (e.g., Excel, digital forms), but collection remains manual and	Key logistics activities (e.g., order intake, inventory changes) are recorded through	Data is automatically captured periodically from operational systems (e.g.,	Real-time data is collected automatically through connected systems (e.g., IoT, GPS, telematics)

	after activities occur. Entry quality and timing are inconsistent.	scattered across staff and processes.	structured digital systems (e.g., applications, barcode scanners), but input still requires user action.	vehicle tracking, automated workflows), reducing human input and ensuring reliable, consistent records.	that adapt dynamically to logistics activities, enabling continuous feedback and live ML input.
Data Storage	Data is stored across individual devices (e.g., laptops, phones, USB drives).	Data is kept in shared folders (e.g., OneDrive), allowing team access, but without system control, structure, or links to core business tools.	Data is stored within separate logistics systems (e.g., WMS, TMS, ERP), but remains siloed in each application without unified access or oversight.	Logistics data is stored in one centralized system (e.g., ERP, or dedicated database).	Data is stored in a scalable storage environment (e.g., database server, cloud storage).
Data Consistency & Quality	Employees record logistics data inconsistently, leading to errors.	Data recording follows a general standard but lacks validation rules.	Automated validation rules ensure accuracy (e.g., duplicate detection, missing data alerts).	Basic automated processing (e.g., outlier detection, missing value handling) ensures high data integrity.	AI-driven data validation continuously corrects anomalies (e.g., fraud detection, real-time error corrections).
Data Integration	Logistics data is siloed across different systems, requiring manual data transfers.	Logistics data can be transferred between systems, but integration is not stable.	Logistics data from different systems can be merged for analytics, even if manual organization is required.	Logistics data from different systems enables smooth and interrupted data communication.	AI-driven logistics models actively utilize integrated data for real-time decision-making.
Historical Data	Historical logistics data is frequently lost, overwritten, or inaccessible.	Historical logistics data is stored separately from active datasets.	Historical logistics data is stored and structured for easy review and basic analysis.	Historical logistics data is stored in a clean, structured, and consistent format, facilitating deeper insights (e.g., KPIs).	ML models continuously update and retrain using historical data, improving accuracy over time.

To achieve ML readiness in the data domain, logistics SMEs must establish foundational capabilities that ensure data is accurate, accessible, and fit for analytical and predictive purposes. This requires a coherent approach that integrates improvements across data collection, storage, quality, integration, and historical availability.

Central to this effort is the progressive automation of data capture. Manual data entry, still prevalent in many logistics' operations, introduces inconsistencies and delays that undermine the reliability required for ML applications. By adopting system-driven mechanisms such as barcode scanners, telematics, or mobile applications, operational events can be recorded in real time, thereby reducing input errors and enabling the creation of more trustworthy datasets. These automation efforts must be embedded within existing workflows to ensure procedural alignment and adoption.

However, data collection alone is insufficient without adequate consolidation. Logistics SMEs often rely on fragmented data environments (dispersed across spreadsheets, paper logs, or siloed software) which impede information flow and inflate the cost of data preparation. Centralizing data into a modular enterprise system, such as an ERP or logistics platform, allows for uniform access and persistent storage, forming a stable foundation for analytical tasks. The consolidation should begin with high-value domains, including order and inventory records, and be supported by structured data migration, staff training, and progressive system deployment.

Ensuring the integrity of the consolidated data is equally critical. Data must be continuously validated for completeness, logical consistency, and adherence to defined formats. Even basic automated routines, such as range checks, anomaly detection, or missing value logs, can substantially reduce downstream cleaning effort and improve the usability of datasets for ML purposes. This not only strengthens the quality of analytical outputs but also embeds a culture of operational discipline around data handling.

The effectiveness of these measures depends on the degree to which systems are integrated. Disconnected tools lead to redundancy, misalignment, and inefficiencies in both operations and ML workflows. SMEs must therefore establish linkages between systems that manage interdependent logistics functions, such as order processing, inventory tracking, and dispatch scheduling, ensuring that key identifiers are shared and updates are synchronized. Initial integration can be manual or semi-automated but should evolve toward real-time interoperability as capabilities mature.

Finally, structured historical data serves as a critical asset for ML training and diagnostic analysis. SMEs should prioritize the consolidation, standardization, and documentation of past logistics records into analyzable formats. Clean historical datasets reduce the effort required for model development, support retrospective evaluation, and reveal performance patterns that guide future interventions.

Table 6 | System & IT Maturity Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
Computational Readiness	Computing infrastructure is limited to basic office tasks. There is no technical ability to run ML tools locally or in a cloud, and no awareness of performance needs for data processing.	General computing resources (e.g., desktop workstations) support daily business operations, but capacity and configuration are not aligned with ML use cases (e.g., insufficient memory, no GPU).	Dedicated shared computing resources are available and suitable for key ML tasks such as data preparation, model testing, and inference. ML-related tasks are planned with infrastructure constraints in mind.	Computing power is matched to specific ML activities. Lightweight inference is performed locally, while heavier tasks (e.g., training or batch processing) are handled by allocated cloud or hybrid resources, ensuring efficiency.	ML workloads are dynamically scheduled and balanced across local and cloud environments using resource orchestration, workload separation, and performance monitoring to maximize cost-efficiency and availability.
Logistics Software & ML Compatibility	Logistics operations rely on standalone tools with no structured data export or system interoperability.	Logistics software systems are in use, although lacking consistent export formats or integration options for ML.	Logistics platforms support structured data exports and basic APIs, enabling ML development and experimentation.	ML models are connected to logistics systems, with outputs feeding directly into planning or operations.	ML capabilities are built into logistics platforms, supporting real-time interaction and continuous learning.
IT Maintenance & Support	No dedicated IT personnel, reliance on	Basic IT support is available but is focused on daily	Dedicated IT support (even if external) ensures	IT infrastructure is proactively monitored,	AI-powered IT maintenance with predictive

	external troubleshooting when issues arise.	operational software rather than system improvements.	system stability, updates, and troubleshooting.	ensuring uptime and system optimization.	diagnostics and automated troubleshooting for continuous system reliability.
IT Adaptability & Future Readiness	No IT development plan. Systems are outdated and there is no awareness of relevant technologies.	Some awareness of IT improvement needs, but no concrete steps or planning in place.	Core systems are stable. Preliminary understanding of ML needs exists, and basic planning has begun.	IT infrastructure is reviewed and upgraded regularly. Scalable systems support ML deployment.	A clear roadmap guides continuous IT evolution. Emerging technologies are monitored and selectively adopted.
Digital Connectivity & Network Maturity	No structured network infrastructure, frequent connectivity issues, reliance on outdated hardware	Basic wired and wireless networks in place, but frequent slowdowns or downtimes occur.	Stable, scalable network infrastructure supports ERP (or logistics software), cloud services, and data exchange with minimal downtime.	High-speed network infrastructure with network monitoring in place.	Optimized network dynamically adjusting bandwidth, prioritizing data flow, and crucial processes.

To establish system and IT maturity as a foundation for machine learning readiness, logistics SMEs must develop a stable, adaptable, and well-supported digital environment. This requires a coordinated approach across computational capacity, software compatibility, system maintenance, long-term adaptability, and network reliability. These elements function interdependently and must be addressed as part of a cohesive digital strategy.

Computational readiness is fundamental. The computing environment, whether local or cloud-based, must support machine learning tasks such as data preprocessing, model training, and inference. For SMEs with limited internal resources, cloud platforms offer a cost-effective alternative. Infrastructure should be planned in accordance with workload demands to prevent disruptions. Basic performance monitoring and scheduled task execution can further optimize system use. Software platforms must support structured data exports and enable integration with external tools. Systems such as ERP, WMS, or TMS should include export formats and API access. Without these capabilities, data preparation becomes inefficient, and model outputs remain disconnected from operations. Compatibility with machine learning requirements should be considered when selecting or renewing systems.

Sustained IT performance depends on proactive maintenance. Support functions (internal or external) must manage updates, security, hardware checks, and backups. These tasks should be scheduled, documented, and supported by issue tracking and escalation procedures to ensure resilience and operational continuity. A long-term IT roadmap is also essential. Existing infrastructure should be audited to identify outdated systems and define upgrade priorities. This roadmap should outline planned investments and integration milestones, enabling SMEs to align system evolution with business and technological developments.

Reliable digital connectivity underpins all system functionality. As logistics SMEs increasingly rely on cloud-based platforms and real-time data exchange, network infrastructure must be stable and scalable. Both internal and external connections should be assessed for coverage, speed, and reliability.

Documentation, bandwidth enhancements, and redundancy solutions such as failover connections strengthen continuity and safeguard digital operations.

Table 7 | Organizational & Cultural Readiness Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
Leadership Buy-In	Company leadership has no understanding of ML and does not see it as relevant to operations.	Leadership is aware of ML's potential but has no structured vision or strategy for its use.	Leadership supports ML adoption and has allocated resources for its implementation.	Leadership integrated ML into long-term strategy, ensuring alignment with business objectives.	Leadership drives AI-first initiatives, fostering innovation and ML-driven improvements.
Workforce Digital Skills	Employees lack basic digital literacy and rely entirely on manual processes.	Some employees have basic digital skills, but no formal training on data-driven decision making.	Employees are trained in using digital tools, and key personnel understand data-driven decision making.	The workforce is proficient in ML-assisted workflows, leveraging automation tools for logistics operations.	Employees continuously upskill in AI and ML applications, adapting to new AI-driven logistics solutions.
Change Management	There is strong resistance to automation and AI-driven decision-making.	Some openness to automation, but no structured change management plan is in place.	A structured change management plan exists, covering transition to automated (or ML-supported) workflows.	ML-driven changes are embraced, with processes continuously optimized based on AI insights.	Change management is embedded in company culture, with employees proactively engaging in AI-driven innovations.
Employees' Opinion	No employees advocate for ML or digital transformation within the company.	A few employees express interest in ML, but no formal AI advocacy or initiatives exist.	Employees actively suggest ML adoption and assist in implementation efforts.	Employees play a key role in scaling AI projects, collaborating with stakeholders, and ensuring adoption.	Employees lead internal AI innovation, continuously exploring new AI-driven solutions for logistics.
IT-Operations Collaboration	There is no collaboration between IT experts and SME. Technology is rarely used to optimize operations.	IT experts and SME interact occasionally but lack a structured approach to using technology for efficiency.	IT experts and SME work together, ensuring practical applications in logistics workflows.	IT-SME collaboration is seamless, with IT solutions directly improving logistics processes.	AI-driven logistics optimization is fully embedded, with IT experts and SME working as a unified, data-driven team.

To establish organizational and cultural readiness for ML adoption, logistics SMEs must align leadership commitment, workforce capabilities, change processes, and internal collaboration. This readiness develops progressively through digital awareness, structured planning, and cooperation between technical and operational roles. The aim is to create an environment where ML initiatives are both feasible and integrated into routine operations.

Leadership must endorse ML as a strategic priority, allocate resources, and initiate pilot projects. When included in innovation strategies and supported by visible actions, this commitment legitimizes experimentation and ensures alignment with business objectives. Clear internal communication reinforces this direction and positions ML as part of the company's digital development. Workforce development supports this commitment. Employees require baseline digital skills to interact effectively with logistics systems, while key personnel should be trained in data-informed decision-making. Targeted upskilling improves data quality, facilitates ML implementation, and reduces dependence on external expertise.

A basic change management plan should be introduced to structure the transition. This includes setting clear objectives, assigning responsibilities, and outlining communication methods. Even brief documentation helps align expectations and maintain continuity, especially in resource-constrained environments. Addressing concerns proactively through transparent updates and targeted support reduces resistance and fosters engagement. Employee involvement enhances practical relevance. Operational staff possess valuable insight into inefficiencies and are well positioned to identify potential ML use cases. Simple mechanisms such as suggestion forms or short team discussions can be used to gather input. Involving employees in small-scale pilots strengthens ownership and promotes adoption, particularly when contributions are recognized.

Finally, collaboration between technical (even if external) and operational experts ensures that ML solutions reflect real-world workflows. Joint problem definition, data exploration, and pilot evaluation facilitate mutual understanding and increase implementation success. Regular check-ins and concise documentation support alignment throughout the development process.

Table 8 | Business Process Readiness Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
Process Standardization	Logistics processes are undocumented, inconsistent, and vary between employees/	Basic process documentation exists, but workflows remain inconsistent among employees.	Logistics processes are standardized, documented, and consistently followed by employees.	Processes are optimized with data-driven insights and predictive analytics.	ML dynamically adapts workflows in real time, optimizing logistics efficiency without human intervention.
Operational Inefficiencies	Frequent bottlenecks, delays, and errors in logistics operations are manually handled with no structured analysis.	SME recognizes inefficiencies but rely on ad-hoc fixes rather than structured process improvements.	Key inefficiencies are identified and addressed using structured workflows and performance metrics.	Data-driven insights optimize operations by predicting inefficiencies and recommending solutions.	Logistics workflows are fully automated with AI-powered optimization, eliminating inefficiencies proactively.
Automation Maturity	Most logistics tasks are manual, with no automation in place.	Some tasks, such as order tracking or inventory updates are partially automated using basic tools.	Core logistics processes, including shipment tracking, inventory updates, and scheduling, are automated.	AI-enhanced automation optimizes task allocation, fleet routing, and resource management.	AI manages logistics processes, dynamically adjusting operations based on real-time data.
Data-Driven Decisions	Operational decisions are based on intuition or past experience rather than data insights.	Some data is used for decision-making, but reports are manually generated and inconsistently applied.	Business decisions are based on structured logistics data, with dashboards providing insights.	Data-driven analytics proactively inform logistics decisions, improving efficiency and cost reduction.	AI processes logistics data, making real-time operational adjustments for continuous improvement.

Performance Monitoring	No formal system exists for tracking logistics performance metrics.	Basic performance tracking is done manually, but reports are infrequent and inconsistent.	Logistics KPIs are defined, tracked, and regularly reviewed to inform process improvements.	Dashboards provide real-time performance monitoring and automated alerts for anomalies.	AI refines performance metrics, automatically identifying trends and optimizing logistics efficiency.

To achieve business process readiness for ML adoption, logistics SMEs must create operational environments that are standardized, structured, and suitable for reliable data use. This requires formalizing workflows, resolving inefficiencies systematically, introducing selective automation, and fostering data-informed decision-making. Together, these practices enable consistent and interpretable operations that support the effective use of ML.

The starting point is the clear documentation of core processes. SMEs should record key workflows such as dispatching, inventory management, or shipment tracking based on actual daily practices. These records must be easy to access and understood by all staff involved. Standardization ensures that tasks are performed consistently, improves data quality, supports onboarding, and facilitates process improvements. Documentation should be kept concise, regularly updated, and integrated into normal routines. Following standardization, procedures to identify and resolve operational inefficiencies should be embedded into existing workflows. SMEs need to define common deviations and create simple, structured responses. Issues such as delivery delays or data entry errors should lead to predefined actions handled by designated staff. This approach supports process stability, improves data reliability, and helps prepare workflows for ML-supported improvements.

Once processes are stable, SMEs should gradually automate repetitive and time-sensitive tasks. Initial automation should focus on areas like shipment tracking, inventory updates, and basic scheduling. Readily available tools, including barcode systems or scheduling applications, can replace manual tasks without the need for large investments. Automation reduces errors, enhances responsiveness, and generates cleaner data. It is essential that pilots involve end-users, follow existing workflows, and include basic training and maintenance support to ensure long-term usability. Alongside automation, SMEs should develop simple dashboards to support operational decision-making. These dashboards should focus on a few key metrics relevant to logistics operations and be updated regularly. Tools may range from spreadsheets to low-cost platforms, depending on technical capacity. Dashboards must be clear, user-friendly, and integrated into routine meetings or shift briefings. Recording how dashboard insights have informed past decisions reinforces their practical value and builds confidence in data use.

The final component is performance monitoring. SMEs should select a small number of key indicators related to their most critical processes. Metrics such as on-time deliveries, picking accuracy, or vehicle use should be easy to track and reviewed consistently. Regular discussions about performance should focus on understanding changes and identifying practical improvements. This continuous review helps strengthen daily operations and builds the data foundation required for machine learning.

Table 9 | Strategic Alignment Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
ML Use Case Fit	No clear understanding of ML or how it	Some awareness of ML use cases but not defined	Specific ML use cases identified based on business needs (e.g.,	ML use cases are integrated into logistics strategy with clear	ML is embedded into core business operations, driving

	applies to logistics operations.	strategy for implementation.	minimizing errors during manual decision-making).	performance goals and KPIs.	optimization and innovation.
Competitive Benchmarking	No assessment of how competitors or industry leaders use ML.	Basic research on industry ML trends, but no structured competitive analysis.	SME has analyzed competitors' ML adoption and identified gaps or opportunities.	SME actively benchmarks ML adoption against peers and adjusts strategy accordingly.	SME leads ML-driven innovation in logistics, influencing industry trends.
Financial Planning	No budget allocated for ML initiatives or unclear financial feasibility.	General understanding of ML investment needs but no structured financial plan.	ML budget is defined, and ROI expectations are assessed before implementation.	SME tracks financial impact of ML applications and adjusts investment strategies based on performance.	ML-driven efficiencies and revenue gains directly influence business growth and long-term financial planning.
Sustainability Alignment	SME has not considered sustainability as a business concern. ML is viewed solely as a tool for operational efficiency or cost reduction.	Sustainability is acknowledged as relevant, but ML is not yet linked to it. Environmental considerations are discussed in general terms but not operationalized.	SME has identified at least one ML use case, supporting environmental performance (e.g. predictive maintenance to minimize waste).	SME actively prioritizes ML use cases that advance sustainability (e.g., emissions reduction, energy-efficiency). Sustainability indicators are factored into performance evaluation of ML pilots.	ML is embedded in SME's sustainability strategy, with clear links to environmental KPIs and long-term impact goals.
Customer Impact	No consideration of how ML adoption affects customer experience.	Initial awareness of ML's potential impact on service quality but no structured approach.	SME has analyzed how ML can improve customer experience (e.g., predictive delivery).	ML-driven enhancements (e.g., dynamic pricing) are actively improving customer satisfaction.	ML-powered insights are used for customer engagement, loyalty programs, and experience optimization.

To establish strategic alignment for ML adoption, logistics SMEs must ensure that ML initiatives support their operational goals, financial constraints, competitive position, sustainability objectives, and customer experience. This alignment requires a deliberate approach that prioritizes relevance, feasibility, and measurable impact.

The process begins with identifying ML use cases that directly address recurring inefficiencies or performance challenges revealed through workflow analysis. Rather than adopting technology based on trends, SMEs should define specific and data-supported business questions. Use cases should be evaluated using simple criteria such as data availability, operational importance, and implementation feasibility. This approach increases the chance of practical success and builds internal commitment. To complement internal assessments, SMEs should also examine how competitors are applying ML. Benchmarking efforts can include reviewing public sources, industry case studies, or innovation reports to identify common applications such as predictive delivery or automated customer updates. These insights help SMEs understand where they stand, recognize opportunities, and avoid outdated or redundant solutions.

Financial planning is a critical element of strategic alignment. SMEs should allocate a realistic budget for ML pilots and estimate returns in tangible operational terms, such as reduced delivery delays or improved inventory accuracy. Budgets may be distributed over phases, and efforts should be made to access external funding or support when available. Defining expected outcomes in advance helps track progress, assess impact, and guide future investment. Sustainability considerations further enhance the strategic value of ML. SMEs should identify where ML can support environmental goals, such as reducing fuel use, preventing waste, or improving energy efficiency. Even if financial gains are limited, sustainability-aligned initiatives can improve regulatory compliance, attract partners, and reinforce reputation. Environmental impact should be included in the criteria used to prioritize ML opportunities.

Customer experience must also be considered. SMEs should analyze key service touchpoints to identify where ML could reduce delays, increase communication clarity, or resolve issues more efficiently. Solutions such as predictive notifications or AI-based support can improve satisfaction and set the business apart. These efforts should be piloted carefully and supported by feedback mechanisms to evaluate their effect.

Table 10 | Security & Regulatory Compliance Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
Data Protection & Privacy	No formal policies for securing logistics data. Data is stored without encryption or access restrictions.	Basic awareness of data security, but no structured approach to protecting logistics data. Sensitive data may be shared or stored improperly.	Data protection policies are in place, and logistics data is securely stored with encryption.	Automated security monitoring and data loss prevention mechanisms are implemented to protect logistics data. Security incidents trigger automated alerts.	AI-powered data protection ensures real-time threat detection, encryption, and automated responses to potential security breaches.
Cybersecurity Measures	No cybersecurity measures in place, making logistics IT systems vulnerable to cyber threats.	Basic IT security measures, such as firewalls and antivirus software, are installed but not actively monitored or updated.	Cybersecurity policies are defined, including network security protocols, firewalls, and regular vulnerability assessments.	Security frameworks are integrated into logistics IT systems, including intrusion detection, endpoint security, and real-time threat monitoring.	Cybersecurity systems autonomously detect and mitigate cyber threats in real time, preventing attacks before they occur.
Regulatory Compliance	No awareness of AI-related regulations or ethical considerations in logistics.	Some understanding of relevant regulations (e.g., GDPR, AI ethics), but no compliance measures in place.	SME has assessed regulatory requirements and ensured ML plans align with legal and ethical guidelines.	Compliance measures are fully integrated into ML governance, ensuring risk mitigation and ethical AI use.	SME proactively engages in regulatory discussions and sets industry best practices for ML ethics and compliance.
Risk Management & Security Governance	No risk management framework exists, leaving logistics IT systems exposed to security breaches.	Basic awareness of security risks, but no structured governance policies or mitigation strategies in place.	Risk assessment processes are in place, including security audits and contingency plans for cyber threats and data breaches.	Security governance is fully integrated, ensuring risk assessments, AI bias audits, and fraud detection mechanisms.	AI-driven governance automates risk detection, policy enforcement, and real-time security adjustments, ensuring compliance and

					operational resilience.
Access Control & Authentication	No restrictions on data access. All employees can view or modify logistics data without authorization.	Some access controls exist, but they are not inconsistent and not strictly enforced, allowing unauthorized access to sensitive logistics data.	Role-based access control (RBAC) is implemented, restricting data access based on employee roles. Multi-factor authentication (MFA) is introduced for key systems.	Centralized identity and access management ensures secure authentication, with audit logs tracking all access to logistics systems.	AI-driven identity management automates access control based on behavioral analysis and risk detection, preventing unauthorized access in real time.

To support ML readiness, logistics SMEs must implement structured practices in security and regulatory compliance. Key focus areas include data protection, cybersecurity, compliance awareness, risk management, and access control. These measures protect digital infrastructure, safeguard sensitive information, and provide a foundation for responsible ML adoption.

Secure data handling begins with clear privacy and protection protocols. SMEs should apply safeguards such as encryption, access restrictions, and basic internal data policies aligned with legal standards, including the GDPR. Operational and personal data, such as customer addresses or delivery logs, must be managed both technically and procedurally. Simple steps like role-based access and brief onboarding sessions ensure that only appropriate personnel handle sensitive information and that good habits are introduced from the outset.

Cybersecurity measures are essential to protect against external threats. These should include a clear cybersecurity policy, enabled firewalls, regular software updates, and periodic vulnerability scans using accessible tools. A designated staff member or support provider should oversee implementation and define procedures for responding to security incidents. Secure remote access, such as the use of VPNs or encrypted applications, helps protect systems when accessed off-site. These actions reduce exposure to threats like phishing, malware, or data breaches that could interrupt ML operations. Regulatory compliance is equally important. SMEs must clarify which data will be used in ML projects, how it is collected and accessed, and what types of decisions are influenced by these systems. This ensures legal and ethical risks are identified and addressed early. Public resources or industry associations can assist in interpreting relevant obligations. Basic ethical principles should also be applied, such as ensuring transparency in automated decision-making or maintaining human oversight of ML outputs.

Risk management reinforces system resilience. SMEs should identify critical digital assets, assess likely threats, and define how risks will be handled. Internal audits and contingency plans help ensure preparedness in the event of disruptions such as system failure or unauthorized access. Clear accountability structures should support decision-making related to security, including periodic reviews of current vulnerabilities and the effectiveness of mitigation strategies. Access control and authentication provide an additional layer of protection. SMEs should assign access rights based on job roles and use multi-factor authentication on all systems managing sensitive data or core operations. These controls must be documented, regularly reviewed, and updated as roles or systems change. Consistent onboarding and offboarding practices reduce the risk of unauthorized access and support operational integrity.

Table 11 | External Dependencies & Ecosystem Readiness Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
Vendor IT Maturity	Logistics partners and suppliers do not use IT solutions, limiting potential collaboration.	Some vendors and partners use IT, but there is no structured approach for integration.	The SME actively engages with IT vendors and ensures compatibility with their systems.	ML-powered vendor collaboration is integrated into operations, enhancing logistics efficiency.	SME leads IT-driven partnerships, influencing industry standards, including AI adoption.
Industry Trends	SME has no awareness of ML adoption trends in the logistics sector.	SME has basic knowledge of industry ML trends but has not assessed their relevance and importance.	SME evaluates ML trends, evaluating their effect on existing processes.	SME actively adapts new IT innovations and aligns strategies with industry's best practices.	SME sets industry standards, contributing to ML innovation and logistics AI advancements.
External Data	SME does not use external data sources for logistics decision-making.	Some external data is manually referenced, but there is no structured integration.	External data sources are integrated into systems.	Data-driven models actively incorporate external data for predictive analytics and optimization.	SME continuously expands external data usage, leveraging diverse AI-driven insights for decision-making.
AI Talent	SME has no access to ML or AI expertise internally or externally.	SME is aware of AI talent needs but has not explored partnerships or hiring strategies.	SME has access to AI expertise through hiring, consulting, or IT-as-a-service providers.	AI talent is embedded within organization, driving ML adoption and strategy.	SME has in-house AI expertise, fostering ML innovation and training.
Research Partnerships	SME does not collaborate with academic or research institutions on IT topics.	There is interest in IT-related research collaborations, but no formal partnerships exist.	SME has established partnerships with universities, AI researchers, or industry groups to support ML initiatives.	SME co-develops data-driven logistics solutions through research collaborations and pilot projects.	SME plays a key role in AI research and logistics innovation, shaping the future of ML adoption in the industry.

To ensure readiness in the category of external dependency and ecosystem readiness, logistics SMEs must strengthen their integration within the broader digital ecosystem. This includes aligning with vendor systems, tracking sector developments, using external data, accessing AI expertise, and forming targeted research partnerships. These actions improve the SME's ability to collaborate, innovate, and adapt to the external factors that influence ML adoption.

A critical first step is assessing the digital maturity of IT vendors. Many ML cases rely on data from external platforms such as fleet management tools, warehouse systems, or IoT devices. If these tools do not support structured data exports, regular updates, or system integration, they hinder ML development. SMEs should maintain a simple checklist evaluating each vendor's data formats, compatibility, and openness to integration. Where issues are identified, SMEs should raise them during vendor discussions and prioritize vendors offering more flexible systems in future contracts. If switching vendors is not an option, lightweight technical solutions can be used to extract or standardize data. Monitoring trends in logistics and AI is also essential. SMEs should stay informed by reviewing sector publications, attending webinars, and observing how other firms apply machine learning. This helps identify relevant use cases and anticipate evolving client expectations. Maintaining a shared record of observations, tagged by topic or technology, can support internal planning. Trend awareness enables SMEs to align their own initiatives with sector developments and avoid outdated or misaligned investments.

External data enhances the value of ML by providing broader context. Data on traffic, weather, fuel prices, or demand cycles can significantly improve model performance. SMEs should identify which external factors influence their operations and determine where reliable data can be accessed. These sources often include public APIs, government datasets, or commercial feeds. Integration does not need to be complex and can start with manual updates or basic scripting. SMEs using modern logistics platforms should also explore whether existing tools already support third-party data inputs. Access to AI expertise is another requirement. SMEs do not need full-time specialists but should secure reliable support through consultants, university partnerships, or digitalization programs. Before engaging external experts, SMEs should clarify their needs and prepare a short overview of their goals, available data, and targeted processes. Experts should be selected based on both technical ability and their capacity to communicate clearly with operational staff. A well-structured collaboration ensures that ML efforts are grounded in practical needs and result in usable outputs.

Research partnerships provide an opportunity to explore machine learning in a controlled and cost-effective way. SMEs can work with academic institutions, applied research groups, or innovation programs to test use cases, validate ideas, or build prototypes. These collaborations often involve student projects or subsidized pilots and can be initiated through a short concept note. SMEs should assign a coordinator to oversee communication, manage expectations, and support knowledge transfer. This allows the partnership to stay focused and aligned with business objectives.

Table 12 | Scalability & Long-Term Viability Assessment Matrix

Category	Level 1	Level 2	Level 3	Level 4	Level 5
IT Scalability	IT systems have hardware or system constraints.	Some digital tools are in place, but systems struggle to scale with growing data and processing needs.	IT infrastructure is scalable, with cloud or hybrid solutions.	ML-driven workloads are dynamically allocated based on demand, optimizing resource use.	Optimized IT infrastructure scales based on real-time logistics demands.
Infrastructure Flexibility	IT infrastructure is outdated and fragmented, relying on manual processes and disconnected software tools.	Some digital upgrades have been made, such as cloud storage or modernized logistics software, but systems remain rigid and difficult to integrate.	IT infrastructure supports modular upgrades and partial system integration, allowing selected ML tools to connect with operational software through structured but limited interfaces.	Infrastructure is interoperable across diverse systems and vendors, enabling adaptable ML deployment and secure data exchange with external platforms, clients, and partners.	Infrastructure evolves into a composable architecture, allowing rapid reconfiguration and plug-and-play ML modules across workflows, partners, and technologies with minimal disruption.
Cost Optimization	No strategy for optimizing IT costs, leading to inefficiencies and	Some awareness of ML-related costs, but no structured financial planning	ML-related costs are assessed, and a cost-effective strategy is in	Cost analysis optimizes IT investments balancing	Cost optimization ensures ML models and IT resources scale

	budget constraints.	for scaling AI solutions.	place to support long-term scaling.	performance and budget efficiency.	efficiently with business growth.
Model Maintenance	No strategy exists for updating or maintaining ML models over time.	Some awareness of model retraining needs, but no structured approach is prepared.	A structured approach is in place for ML model monitoring, retraining, and version control.	ML models are automatically retrained based on new logistics data, minimizing performance degradation.	AI autonomously manages model lifecycle, adapting to changing logistics patterns and data trends.
Project Governance	No governance frameworks are utilized, increasing operational and compliance risks.	Basic governance policies exist, but they are not consistently enforced.	A structured governance framework is established, ensuring compliance, security, and responsible data / AI usage.	Governance policies are automated and dynamically updated based on regulatory and business changes.	AI-driven governance systems proactively enforce policies and compliance measures across all ML applications.

To prepare for the adoption of ML and to ensure it is scalable and long-term viable, logistics SMEs must ensure that machine learning initiatives are capable of expanding and remaining effective over time. This involves scaling infrastructure, enabling integration with existing systems, controlling costs, maintaining model performance, and formalizing governance. These measures support the continued relevance and sustainability of ML use as the business evolves.

Scalability begins with evaluating the capacity of IT infrastructure to handle increasing data and processing needs. SMEs should assess whether current systems are sufficient for ML workloads and consider using cloud-based or hybrid solutions where necessary. Modular cloud services offer flexible and cost-efficient options without requiring large upfront investment. Infrastructure performance should be reviewed periodically to ensure that storage, processing power, and connectivity remain sufficient as demand grows. At the same time, infrastructure must remain flexible. SMEs should avoid full system replacements by enabling modular integrations that allow ML tools to interact with logistics systems. Structured data exports, basic interfaces, and low-code solutions can be used to connect ML components to existing workflows. This approach supports gradual adoption and minimizes disruption while maintaining the stability of core operations.

Managing costs is essential for long-term viability. SMEs should track both direct costs, such as software and infrastructure, and indirect costs, such as time spent by staff and external consultants. These costs should be reviewed regularly to identify unnecessary spending or inefficiencies. ML should be introduced in stages, beginning with areas that offer the highest impact. External funding and partnerships can help reduce the financial burden during early phases of adoption. Ongoing model maintenance is also required. ML systems must be monitored for performance and retrained as conditions change. SMEs should define relevant performance indicators, establish clear retraining criteria, and document model versions to maintain clarity over time. Maintenance does not require complex tools but should be consistent and aligned with daily operations. Before a model is fully deployed, updates should be tested in a controlled setting to confirm reliability.

Finally, governance provides the structure needed to oversee long-term ML use. SMEs should assign responsibilities for approving ML initiatives, monitoring outcomes, and managing implementation. These roles and processes can be outlined in a simple internal document. Regular reviews should assess model performance, collect feedback from users, and identify necessary adjustments. Basic ethical safeguards should also be defined to ensure that ML supports, rather than replaces, human decision-making in sensitive contexts.

Once readiness across all eight categories has been established, logistics SMEs must move from assessment to execution. This requires coordinated action across internal consolidation, strategic alignment, and structured pilot implementation. Each domain supports sustainable and effective machine learning integration.

To ensure operational alignment, SMEs should appoint internal champions from IT, operations, or data-focused roles to lead ML initiatives. These individuals translate business needs into ML use cases and coordinate implementation. Basic data governance procedures must also be defined, including model review, retraining protocols, and error handling. Lightweight tools such as spreadsheets, version tracking, and data backups can support these routines. To monitor progress, SMEs should introduce performance indicators. These should measure both model effectiveness, such as forecast accuracy, and organizational learning, such as staff participation and use of model outputs. This supports transparency and reinforces accountability.

ML projects must align with strategic business objectives. SMEs should review their medium-term goals and identify use cases with clear value, such as in planning, forecasting, or service optimization. Each case must meet three conditions: available historical data, measurable outcomes, and implementation feasibility. Projects should be prioritized accordingly. A cross-functional steering group should oversee ML initiatives, including representatives from management, operations, IT, and customer service. This group approves, monitors, and adjusts initiatives to maintain alignment with broader digital strategy.

Pilots provide a controlled environment to test ML use cases. Each pilot should focus on a specific business challenge, involve a limited user group, and run alongside existing systems for comparison. Data pipelines must be finalized beforehand, and computing resources secured. A small team should manage the pilot. SMEs must retain ownership of data and business logic, with clear agreements on model retraining, reuse, and intellectual property. Evaluation must consider both technical performance and operational relevance. Findings should be documented to guide next steps.

After a successful pilot, SMEs should integrate ML into regular operations. This includes staff retraining, workflow updates, and resource planning for further development. Adoption should shift from isolated pilots to a systematic exploration of new ML opportunities. A feedback culture must be established. Employees should report discrepancies between output and real-world conditions. Processes must support retraining, adaptation, and periodic audits to monitor model relevance and performance. SMEs should also engage with external networks to access shared resources, industry benchmarks, and collaborative opportunities. This external engagement accelerates innovation and supports the long-term success of ML integration.

To examine the practical application of the proposed ML preparation & readiness assessment framework to real-world problems, refer to **section Appendices – Case Studies**.

B) Readiness Measurement Across Frameworks

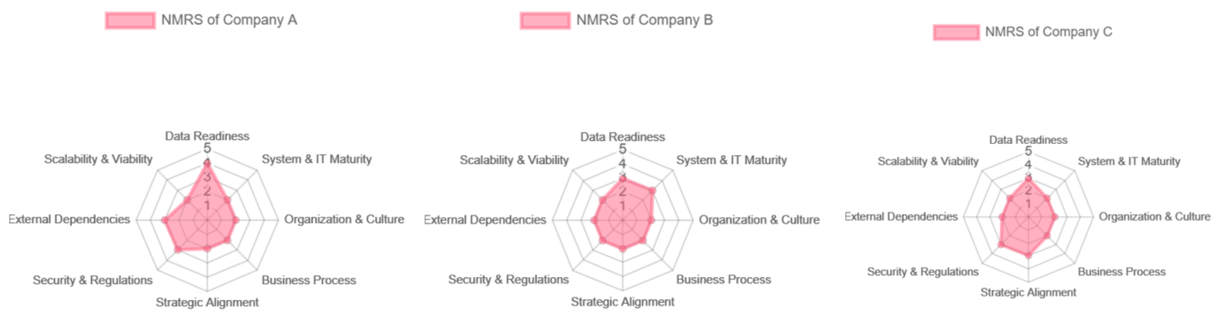

Figure 4 | Normalized ML Readiness Score Across SME Participants

After determining the NMRS for the three participating SMEs, based on their category-level evaluations as presented in Figure 4, these values are compared with readiness indexes derived from existing AI readiness assessment frameworks. The purpose of this comparison, shown in Table 13, is to examine whether the NMRS is consistent with external measures of ML readiness. The approach supports a cross-framework validation of the NMRS and provides insight into the degree of convergence or divergence in how readiness is defined and assessed across different methods.

Table 13 | Comparison of Readiness Indexes Across Assessment Frameworks

Framework / Organization	ML Preparation & Readiness Assessment SME Framework	Strategic AI Adoption SME Prescriptive Framework	Cisco AI Readiness Index	AI Readiness in Malaysian SMEs Framework	Organizational Readiness Framework
Company A	0.375	0.467	0.33	0.443	0.378
Company B	0.3125	0.333	0.23	0.223	0.200
Company C	0.344	0.450	0.29	0.390	0.333

After normalizing the results to the 0 to 1 scale proposed in this study, two key insights emerge. First, none of the assessed logistics-oriented SMEs reach the threshold of full readiness, indicating that significant preparation remains necessary before ML can be implemented effectively. This outcome is expected, as several of the compared frameworks are not tailored to the SME context and may reflect requirements suited to larger enterprises.

Second, despite variations in absolute values, all frameworks display a similar trend. Company A consistently shows the highest readiness, followed by Company C, with Company B ranking lowest. This pattern supports the internal consistency and reliability of the proposed ML Preparation and Readiness Assessment SME Framework introduced in the study.

Detailed Results? Appendix?

C) Guidance Evaluation

A

VII. Limitations

A

- Simulated Environment – due to time, etc.
- Limited Data Points of Feedback

VIII. Discussion & Future Work

- Discuss results from subsection B and C

-Discuss that most raediness frameworks don't have a specific readiness index. They are structured as a flexible and adaptable assessment tool meant for qualitative and semi-qualititive evaluation. Their focus lies in identifying and organizing relevant readiness components, although in most existing frameworks, an actual measurement and scoring requires an additional operational layer that is not designed, whereas it is done in my framework.

- Discuss how also my framework is a combination of technical, strategical and sociopsychological aspects. Other frameworks usually focus on only one of these.

- Discuss how there are very small amount of frameworks targeted at SMEs, and none for logistics companies in general, kamoli logistics SMEs.

- Discuss how some existing frameworks for preparation provide guidance for companies targeted after when a company is considered ready and assuming everything is in order to adopt ML.

- Discuss how all frameworks state guidance as to what is advised, some state why is it advised, but ONLY 2 state how to follow-up on the advice that was given.

- Discussion should focus on the different applications of the framework and how it could turn out to benefit the logistics SMEs. Example would be how Greenzone and logicall are totally different logistics companies with different products, goals, and strategies but are on different ends of the same problem. Due to manual decision-making, based on intuition and experience and not data-driven insights and prediction, one of the companies suffers from understocking, while the other from overstocking.
- Future work should involve the application of the framework in the real field.
- The framework has potential to be transformed into a framework from SMEs in different fields.

IX. Conclusion

- 2 sentences per chapter, NO NEW REFERENCES

X. References

[1] European Comission, "Europe's Digital Decade: digital targets for 2030," [Online]. Available: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/europes-digital-decade-digital-targets-2030_en?utm_source=chatgpt.com. [Accessed 11 02 2025].

[2] European Comission, "2030 Digital Compass: the European way for the Digital Decade, COM(2021) 118 final," European Comission, Brussels, 2021.

[3] A. L. Gómez and S. J. López, "Innovation and Transformation: Keys to the Success of SMEs in the

Digital Age," *Journal of Economics, Innovative Management and Entrepreneurship,* vol. 2, no. 3, 2024.

[4] R. Kepczynski, A. Ghita, R. Jandhyala, G. Sankaran and A. Boyle, "Enable IBP with SAP Integrated Business Planning," in *Implementing Integrated Business Planning*, Springer, 2018, pp. 23-110.

[5] D. Andayani, "Leveraging AI-Powered Automation for Enhanced Operational Efficiency in Small and Medium Enterprises (SME)," *APTISI Transactions on Management (ATM),* vol. 8, no. 3, pp. 250-258, 2024.

[6] M. Archana, "Study on the ERP Implementation Methodologies on SAP, Oracle NetSuite, and Microsoft Dynamics 365: A Review," 2022.

[7] I. Hamburg and S. Bucksch, "Cloud Computing in SMEs," in *ICIW 2016 : The Eleventh International Conference on Internet and Web Applications and Services*, 2016.

[8] O. Issah, "Logistics Capabilities, Supply Chain Performance and SMEs Sustainability: the moderating effect of Digital Technology," *African Journal of Procurement, Logistics & ,* vol. 8, no. 1, pp. 89-107, 2025.

[9] K. E. Knutsen, Q. Liang, N. Karandikar, I. Ibrahim, X. Tong and J. J. H. Tam, "Containerized immutable maritime data sharing utilizing Distributed Ledger Technologies," *Journal of Physics: Conference Series,* vol. 2311, 2022.

[10] Y. S. Balcıoğlu, "Integrating Blockchain Technology in Supply Chain Management: A Bibliometric Analysis of Theme Extraction via Text Mining," *Sustainability,* vol. 16, no. 22, 2024.

[11] N. Syynimaa, "Exploring Azure Active Directory Attack Surface: Enumerating Authentication Methods with Open-Source Intelligence Tools," 2022.

[12] A. Papathanasiou, "Cybersecurity Guide for SMEs: Protecting Small and Medium-Sized Enterprises in the Digital Era," *Journal of Information Security,* vol. 16, no. 1, pp. 1-43, 2025.

[13] America's Seed Fund, "The Impact of Cyber Security on Small Businesses," America's Seed Fund.

[14] S. Sharma, "Significance of E-Commerce in the Growth and Development of Small Businesses: A Qualitative Study," *Journal of Cardiovascular Disease Research,* vol. 12, no. 2, 2021.

[15] T. Mazzarol, "SMEs engagement with e-commerce, e-business and e-marketing," *Small Enterprise Research,* vol. 22, pp. 79-90, 2015.

[16] W. Allen, "The Logistics Revolution and Transportation," *The ANNALS of the American Academy of Political and Social Science,* vol. 553, pp. 106-116, 1997.

[17] J. He, "Digital transformation and supply chain efficiency improvement: An empirical study from a-share listed companies in China," *PLoS ONE,* vol. 19, no. 4, 2024.

[18] I. Akpan and E. Udoh, "Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic," *Journal of Small Business and Entrepreneurship,* vol. 34, pp. 123-140, 2020.

[19] D. Egorov, A. Levina, S. Kalyazina, P. Schuur and B. Gerrits, "The Challenges of the Logistics Industry in the Era of Digital Transformation," Saint-Petersburg, 2020.

[20] D. Aghazadeh and G. A. Akyuz, "Machine Learning (ML) in Logistics and Supply Chain Management (SCM)," in *6th European International Conference on Industrial Engineering and Operations Management*, 2022.

[21] A. Odimarha, S. Ayodeji and E. Abaku, "MACHINE LEARNING'S INFLUENCE ON SUPPLY CHAIN AND LOGISTICS OPTIMIZATION IN THE OIL AND GAS SECTOR: A COMPREHENSIVE ANALYSIS," *Computer Science & IT Research Journal,* vol. 5, no. 3, pp. 725-740, 2024.

[22] European Comission, "Definition of SME," 2020. [Online]. Available: https://single-market-economy.ec.europa.eu/smes/sme-fundamentals/sme-definition_en. [Accessed 17 02 2025].

[23] S. Bell, "Small and medium enterprises (SMEs) finance," The World Bank Brief, available at: https://www.worldbank.org/en/topic/smefinance, 2015.

[24] M. Dabić, "Pathways of SME internationalization: a bibliometric and systematic review," 2019.

[25] European Comission, "European SMEs under Pressure," European Comission, 2009.

[26] C. Begg and T. Caira, "Exploring the SME Quandary: Data Governance in Practice in the Small to Medium-Sized Enterprise Sector," 2012.

[27] T. Henschel and I. Heinze, "Small and Medium-sized Enterprises (SMEs)," 2018.

[28] J. Wiklund and D. Shepherd, "Knowledge-based resources, entrepreneurial orientation, and performance of small and medium-sized businesses,"

Stategic Management Journal, vol. 24, pp. 1307-1314, 2003.

[29] D. Carson and A. Gilmore, "SME marketing management competencies," *International Business Review,* vol. 9, no. 3, pp. 363-382, 2000.

[30] D. M. Macrì, M. R. Tagliaventi and F. Bertolotti, "Sociometric location and innovation: how the social network intervenes between the structural position of early adopters and changes in the power map," *Technovation,* vol. 21, no. 1, pp. 1-13, 2001.

[31] R. Thorpe, R. Holt, A. Macpherson and L. Pittaway, "Using Knowledge within Small and Medium-Sized firms: A systematic review of the evidence," *International Journal of Management Reviews,* vol. 7, no. 4, pp. 257-281, 2005.

[32] G. Ceyhun and H. Keser, "Introduction to International Transportation and Logistics," *Handbook of Research on the Applications of International Transportation and Logistics for World Trade,* p. 17, 2020.

[33] C. Wang, "Spatial Organizational Network of Loigsitcs Company in China," *Acta Geographica Sinica,* vol. 63, no. 2, pp. 135-146, 2008.

[34] A. Vasanthy and S. Chandramohan, "Logistics – Conceptual Approach," *International Journal of Research Publication and Reviews,* 2023.

[35] T. Crainic, "Long-Haul Transportation Freight Transportation," *Handbook of Transportation Science,* pp. 451-516, 2003.

[36] R. Sivitanidou, "Warehouse and distribution facilities and community attributes: An Emperical Study," *Environment and Planning,* vol. 28, no. 7, pp. 1261-1278, 1996.

[37] K. Tan, S. Lyman and J. Wisner, "Supply chain management: a strategic perspective," *International Journal of Operations & Production Management,* vol. 22, no. 6, pp. 614-631, 2002.

[38] K. Rao and R. R. Young, "Global Supply Chains," *International Journal of Physical Distribution & Logistics Management,* vol. 24, no. 6, pp. 11-19, 1994.

[39] M. Heutger and M. Kueckelhaus, "Digital Twins in Logistics," DHL Trend Research, 2021.

[40] S. Wong, J. Yeung, Y.-Y. Lau and T. Kawasaki, "A Case Study of How Maersk Adopts Cloud-Based Blockchain Integrated with Machine Learning for Sustainable Practices," *Sustanability,* vol. 15, no. 9, 2023.

[41] M. Kress, Operational Logistics, Springer, 2016.

[42] C. Tzitzikostas, "From the Green Deal to the Clean Industrial Deal," in *Transport & Environment event*, 2025.

[43] C. Holland, J. Levis, R. Nuggehalli, B. Santili and J. Winters, "UPS Optimizes Delivery Routes," *Informs Journal on Applied Analytics,* vol. 47, no. 1, 2017.

[44] W. Manaviriyaphap, "AI-Driven Optimization Techniques in Warehouse Operations: Inventory, Space, and Workflow Management," *Journal of Social Science and Multidisciplinary Research,* vol. 1, no. 4, 2024.

[45] M. Norrie, "An Introduction to Machine Learning," in *Data Analytics*, CRC Press, 2018, p. 13.

[46] Y. Liu, "Natural Language Processing in Data Analytics," in *Data Analytics and AI*, CRC Press, 2020.

[47] X.-w. Chen and X. Lin, "Big Data Deep Learning: Challenges and Perspectives," *IEEE Access,* 2014.

[48] N. Kumar, "Review Paper on Machine Learning Algorithms," *International Journal of Scientific Research in Engineering and Management,* vol. 9, no. 3, 2025.

[49] B. Muter and A. Mohammed, "The Future of AI: Assessing the Strengths and Limitations of Deep Learning and Machine Learning," vol. 4, no. 6, 2024.

[50] R. Caruana and A. Niculescu-Mizil, "An empirical comparison of supervised learning algorithms," in *ICML '06: Proceedings of the 23rd international conference on Machine learning*, 2006.

[51] Q. Wen, L. Hua and A. John, "Comparative Analysis of Machine Learning Algorithms for Optimizing Computational Efficiency in AI Systems," 2024.

[52] N. Brown, "Enhancing Trust in LLMs: Algorithms for Comparing and Interpreting LLMs," arXiv, 2024.

[53] J. Gafur, S. Goddard and W. Lai, "Adversarial Robustness and Explainability of Machine Learning Models," in *PEARC '24: Practice and Experience in Advanced Research Computing*, Providence, RI, USA, 2024.

[54] S. Shalev-Shwartz, "Online Learning and Online Convex Optimization," *Foudnations and Trends in Machine Learning,* vol. 4, no. 2, pp. 107-194, 2012.

[55] L. Kaelbling, M. Littman and A. Moore, "Reinforcement Learning: A Survey," *J. Artif. Intell. Res.,* vol. 4, pp. 237-285, 1996.

[56] M. S. Soudi and M. Bauters, "AI Guidelines and Ethical Readiness Inside SMEs: A Review and Recommendations," *Digital Society,* vol. 3, no. 3, 2024.

[57] W. T. M. Yen, T. L. Hong and Y. Y. Yen, "A Proposed Framework for Assessing the Readiness of AI in Small and Medium Enterprises (SMEs) in Malaysia," *Journal of Ecohumanism,* vol. 3, no. 5, pp. 254-260, 2024.

[58] K. Hiniduma, S. Byna, J. L. Bez and R. Madduri, "AI Data Readiness Inspector (AIDRIN) for Quantitative Assessment of Data Readiness for AI," 2024.

[59] Cisco, "Cisco AI Readiness Index: Hype Meets Reality," Cisco, 2024.

[60] A. Lavin, C. M. Gilligan-Lee and A. Visnjic, "Technology readiness levels for machine learning systems," *Nat Commun,* 2022.

[61] U. Lichtenthaler, "Five Maturity Levels of Managing AI: From Isolated Ignorance to Integrate Intelligence," *Journal of Innovation Management,* vol. 8, no. 1, pp. 39-50, 2020.

[62] J. Holmstrom, "From AI to digital transformation: The AI readiness framework," *Business Horizons,* vol. 65, pp. 329-339, 2022.

[63] M. Palade and G. Carutasu, "Organizational Readiness for Artificial Intelligence Adoption," *Transactions on Engineering and Management,* vol. 7, no. 1&2, 2021.

[64] M. A. Nortje and S. S. Grobbelaar, "A Framework for the Implementation of Artificial Intelligence in Business Enterprises: A Readiness Model," Auckland University of Technology, 2020.

[65] A. Najdawi, "Assessing AI Readiness Across Organizations: The Case of UAE," Carleton University, 2020.

[66] J. Baker, "The Technology–Organization–Environment Framework," University of Hamburg, Hamburg, Germany, 2011.

[67] J. García-Avilés, "Diffusion of Innovation," in *The International Encyclopedia of Media Psychology*, John Wiley & Sons, 2020, pp. 1-8.

[68] P. Burggraf, F. Steinberg, C. Sauer and P. Nettesheim, "Machine learning implementation in small and medium-sized enterprises: insights and recommendations from a quantitive study," *Production Engineering,* vol. 18, pp. 751-764, 2024.

[69] J. Otterbach and T. Wollmann, "Chameleon: A Semi-AutoML framework targeting quick and scalable development and deployment of production-ready ML systems for SMEs," 2021.

[70] S. Badghish and Y. A. Soomro, "Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology-Organization-Environment Framework," *Sustainability,* vol. 16, 2024.

[71] A. Hussain and R. Rizwan, "Strategic AI adoption in SMEs: A Prescriptive Framework," 2024.

[72] J. Schwaeke, A. Peters, D. Kanbach, S. Kraus and P. Jones, "The new normal: The status quo of AI adoption in SMEs," *Journal of Small Business Management,* pp. 1-35, 2024.

[73] U. Chakraborty, "Building Blocks of an AI Framework for an Enterprise," SSRN, 2020.

[74] K. Schuler and D. Schlegel, "A Framework for Corporate Artificial Intelligence Strategy," in *Digital Economy: Emerging Technologies and Business Innovation*, Springer, 2021, pp. 121-133.

[75] E. Makarius, D. Mukherjee, J. Fox and A. Fox, "Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization," *Journal of Business Research,* vol. 120, pp. 262-273, 2020.

[76] A. McKinnon and M. Piecyk, "Setting targets for reducing carbon emissions from logistics: current practice and guiding principles," *Carbon Management,* vol. 3, no. 6, pp. 629-639, 2012.

[77] P. Fajgelbaum, "The Value of De Minimis Imports," Natuional Bureau of Economic Research, Cambridge, The USA, 2024.

[78] A. C. Odimarha, "Securing the digital supply chain: Cybersecurity best practices for logistics and shipping companies," *World Journal of Advanced Science and Technology,* vol. 5, no. 1, pp. 26-33, 2024.

[79] P. Illanes, S. Lund, M. Mourshed, S. Rutherford and M. Tyreman, "Retraining and reskilling workers in the age of automation," McKinsey Global Institute, 2018.

[80] R. Boute and M. Udenio, "AI in Logistics and Supply Chain Management," in *Global Logistics and Supply Chain Strategies for the 2020s*, Springer, 2022, pp. 49-65.

[81] L. Xin, P. Xu and G. Manyi, "Logistics Distribution Route Optimization Based on Genetic Algorithm," *Computational Intelligence and Neuroscience,* 2022.

[82] E. I. K. Tijan and M. Jardas, "Blockchain Technology Implementation in Logistics," *Sustainability,* vol. 11, no. 4, 2019.

[83] T. Althaqafi, "Assessing the Evolving Role of Geopolitical Risks in Supply Chain Logistics: An Empirical Analysis of Risk Management Strategies," *International Journal of Computing and Digital Systems,* vol. 17, no. 1, pp. 1-14, 2024.

[84] C. Saller and F. Kluhr, "Financing Disruption - The Role of Venture Capital in the Logistics Industry," in *Disrupting Logistics*, Springer, 2021, pp. 279-290.

[85] M. Uddin, S. Anowar and N. Eluru, "Modeling Freight Mode Choice Using Machine Learning Classifiers: A Comparative Study Using the Commodity Flow Survey (CFS) Data," *Transportation Planning and Technology,* vol. 44, no. 5, pp. 543-559, 2024.

[86] H.-i. Ahn, S. Olivar, H. Mehta and Y. C. Song, "Generative Probabilistic Planning for Optimizing Supply Chain Networks," noodle AI, San Francisco, CA.

[87] B. Zhu and C. Vuppalapati, "Overcoming Supply Chain Challenges with Advanced Machine Learning: exploring the Potential of Deep Meta-Learning and Multi-Task Learning," in *2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE)*, 2023.

[88] Y. Liu, Q. Ye, Y. Feng, J. Escribano-Marcias and P. Angeloudis, "Location-routing Optimisation for Urban Logistics Using Mobile Parcel Locker Based on Hybrid Q-Learning Algorithm," in *Transportation Research Board 101st Annual Meeting (TRBAM 2022)*, 2021.

[89] T. Doernbach, "Self-Supervised Damage-Avoiding Manipulation Strategy Optimization via Mental Simulation," *Intelligent Service Robotics,* 2017.

[90] H. Chai and Y. Liang, "A novel logistic regression model combining semi-supervised learning and active learning for disease classification," *Scientific Reports 8,* vol. 13009, 2018.

[91] M. C. Camur, S. K. Ravi and S. Saleh, "Enhancing Supply Chain Resilience: A Machine Learning Approach for Predicting Product Availability Dates Under Disruption," 2023.

[92] M. Gholipour, "The Impact of Machine Learning Algorithms and Big Data on Privacy in Data Collection and Analysis," *Canadian Journal of Business and Information Studies,* vol. 6, no. 5, pp. 93-103, 2024.

[93] A. Lakhani and N. Rohit, "Securing Machine Learning: Understanding Adversarial Attacks and Bias Mitigation," *International Journal of Innovative Science and Research Technology,* vol. 9, no. 6, 2024.

[94] V. Franzoni, "From Black Box to Glass Box: Advancing Transparency in Artificial Intelligence Systems for Ethical and Trustworthy AI," *Computational Science and Its Applications – ICCSA 2023 Workshops,* pp. 118-130, 2023.

[95] K. Dodiya, S. Radadia and D. Parikh, "Differential Privacy Techniuqes in Machine Learning for Enhanced Privacy Preservation," *JETIR,* vol. 11, no. 2, 2024.

[96] D. Sudrajat, S. Candra and A. Handrimurtjahjo, "The Importance of Innovative Logistics Service Capabilities for Assets-based Logistics Service Providers," in *2nd International Conference on Inclusive Business in the Changing World ICIB*, 2019.

[97] Q. Wan, Y. Yuan and F. Lai, "Disentangling the driving factors of logistics outsourcing: a configurational perspective," *Journal of Enterprise Information Management,* vol. 32, no. 6, pp. 964-992, 2019.

[98] W. Stölzle and L. Häberle, "Digital Logistics Platforms—Initial Approaches to Market Segmentation in Light of Traditional and New Providers," in *Lessons Learned from Industry 4.0 Across Europe*, Springer, 2021, pp. 105-123.

[99] C. Martinez-Olvera, "Impact of Hybrid Business Models in the Supply Chain Performance," *Supply Chain,* 2008.

[100] J. Soh and P. Singh, "Machine Learning Operations," *Data Science Solutions on Azure,* 2022.

[101] P. Burggraf, F. Steinberg, C. R. Sauer and P. Nettesheim, "Machine learning implementation in small and medium-sized enterprises: insights and recommendations from a quantitive study," 2024.

[102] A.-R. Tawil, X. Schmoor, K. Vlachos and D. Haidar, "Trends and Challenges Towards an Effective Data-Driven Decision Making in UK SMEs: Case Studies and Lessons Learnt from the Analysis of 85 SMEs," 2023.

[103] R. Saravanan and P. Sujatha, "A State of Art Techniques on Machine Learning Algorithms: A perspective of Supervised Learning Approaches in Data Classification," in *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2018.

XI. Appendices

A) Glossary

a

B) Challenges in Logistics

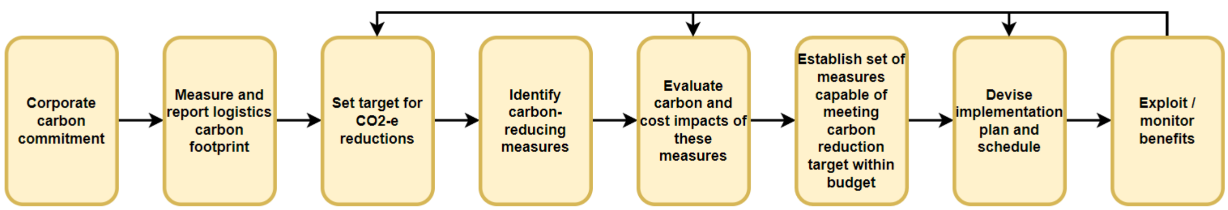

Figure 5 | Stages in the development of a decarbonization strategy for logistics

To address the challenges logistics companies face, they must invest in infrastructure expansion, the enhancement of port capacity, and the integration of digital solutions. The adoption of automation, predictive analytics, and smart logistics technologies is essential for maintaining operational efficiency, reducing costs, and adapting to shifting market demands.

Logistics companies are increasingly adopting carbon reduction strategies, as depicted in Figure 3, including energy-efficient technologies, optimized transport routes, and alternative fuels, to comply with environmental regulations while improving efficiency and cost savings [65]. Trade restrictions and shifting import-export regulations, such as changes to the U.S. "de minimis" rule, add complexity to supply chain management, requiring firms to invest in compliance programs, AI-driven tracking, and regulatory partnerships [66].

The digitization of logistics has heightened cybersecurity risks, making data breaches, ransomware, and phishing threats key concerns. Companies must implement robust security frameworks and employee training to mitigate these vulnerabilities [67]. Meanwhile, automation is redefining logistics jobs, as AI-driven systems manage inventory, route optimization, and fulfillment. While this improves efficiency, it necessitates workforce reskilling to adapt to technology-driven roles [68].

AI and predictive analytics enhance demand forecasting, inventory management, and route efficiency, reducing costs and optimizing deliveries [69, 70]. Blockchain and digital freight platforms improve transparency and automate transactions, optimizing freight matching and reducing inefficiencies [71].

Sustainability initiatives, including electric vehicles and renewable energy, are shaping the future of logistics alongside geopolitical risks that require adaptive supply chain strategies [72]. Venture capital investments in autonomous delivery, AI logistics, and digital platforms continue to drive industry innovation [73]. Logistics companies must balance regulatory compliance, digital transformation, and sustainability to remain competitive in a rapidly evolving global market.

C) ML in Logistics

The integration of machine learning (ML) in logistics has significantly improved efficiency, resilience, and decision-making by addressing key challenges such as route optimization, inventory management, and predictive analytics. Various ML techniques have been tailored to meet distinct logistics needs, demonstrating superior performance over traditional models.

Ensemble learning, particularly Random Forest and Gradient Boosting, has enhanced freight mode choice prediction, outperforming traditional multinomial logit models by leveraging shipment characteristics such as distance, industry classification, and size [53]. Generative learning has optimized supply chain planning under uncertainty, with Generative Probabilistic Planning (GPP) reducing lost sales by seventy-five percent and excess stock by twenty percent through attention-based graph neural networks [54].

Meta-learning and multi-task learning facilitate adaptive supply chain management, particularly in shipping cost prediction, by enabling rapid adaptation with limited data [55]. Reinforcement learning has optimized urban logistics, improving last-mile delivery efficiency through a hybrid Q-learning algorithm [56]. Self-supervised learning enhances damage-avoidance strategies, refining autonomous handling of fragile goods without human intervention [57]. Semi-supervised learning addresses data scarcity challenges, combining labeled and unlabeled data to improve inventory prediction and demand forecasting [58].

Tree-based models, such as Random Forest and Gradient Boosting, have proven effective in predicting product availability during supply chain disruptions. A case study by General Electric Gas Power demonstrated their superiority over traditional regression models, enhancing logistics planning and reducing transportation costs [59]. These findings underscore machine learning's transformative role in logistics, ensuring greater adaptability and operational efficiency in a rapidly evolving industry.

D) Privacy, Security, and Ethical Considerations

The extensive use of personal data in machine learning raises critical concerns regarding privacy, security, and ethics. The collection and analysis of sensitive information introduce risks of unauthorized access, data breaches, and misuse, necessitating stringent protection measures to maintain public trust and legal compliance [74].

Security vulnerabilities, including adversarial attacks designed to manipulate AI models, threaten the integrity of machine learning applications, particularly in finance and healthcare. Additionally, reliance on large datasets poses risks related to data provenance and embedded biases, potentially reinforcing societal inequalities. Addressing these challenges requires continuous monitoring and robust safeguards [75].

Ethical concerns extend to bias, accountability, and transparency. Machine learning models can perpetuate discrimination if trained on biased data, while black-box models reduce transparency, limiting the ability to understand or contest AI decisions. Ensuring fairness and explainability is essential to maintaining trust in AI systems [76].

To mitigate these risks, privacy-preserving techniques such as differential privacy, federated learning, and homomorphic encryption aim to protect data while maintaining analytical utility. Embedding ethical frameworks and security measures into AI development promotes responsible and trustworthy machine learning practices [77].

E) Additional ML information

ML / Criteria	Performance and Accuracy	Efficiency and Computational Complexity	Data Dependency and Sample Efficiency	Interpretability and Explainability	Adaptability and Transferability	Ethical Considerations and Bias Mitigation	Cost and Implementation Feasibility	Resilience to Adversarial Attacks
Time-Series Forecasting Invalid source specified.	High performance in temporal pattern prediction with sufficient historical data, ensuring reliable demand forecasting.	Efficient for structured time-series data but computationally intensive for large datasets and deep learning models.	Heavily reliant on extensive historical data, with performance degrading when time-series continuity is disrupted.	High interpretability in traditional models like ARIMA, but reduced explainability in deep learning approaches such as LSTMs and transformers.	Limited adaptability to new datasets, with low transferability across domains, often requiring retraining for different time-series applications.	Less prone to societal biases but can reinforce historical data biases, potentially leading to inaccurate or unfair forecasting outcomes.	Implementation costs vary depending on data preprocessing and model complexity, with higher costs for deep learning-based forecasting.	Vulnerable to adversarial manipulation, as small perturbations in historical data can significantly impact future predictions.
Online Learning [51]	Accuracy depends on data stream quality and often requires adaptive algorithms to ensure consistency.	Efficient for real-time processing but depends on adaptive algorithms to handle complexity.	Efficiency relies on a continuous stream of high-quality data, but concept drift can diminish effectiveness over time.	Interpretability varies by algorithm, with adaptive models favoring performance over explainability.	Highly adaptive to dynamic environments but vulnerable to concept drift if data distribution changes are not properly managed.	Prone to bias if real-time data streams reinforce societal inequalities or propagate misinformation.	Cost-effective for continuous data streams but increases when adapting to concept drift.	Vulnerable to concept drift and adversarial influences in data streams.
Reinforce-ment Learning [52]	High accuracy in dynamic environments but reliant on reward design and exploration strategies.	Computationally demanding due to iterative exploration and reward optimization.	Requires extensive environmental interaction for learning, with low sample efficiency due to its trial-and-error approach.	Decision-making is difficult to explain due to complex reward structures and policy learning.	Highly adaptive in familiar settings but struggles with transferability unless reward functions and policies are aligned.	Biases can arise from reward structures, leading to ethically problematic behaviors if objectives are misaligned.	High implementation costs due to computational demands and environment simulation requirements.	Vulnerable to adversarial policies that exploit reward functions.

ML / Criteria	Performance and Accuracy	Efficiency and Computational Complexity	Data Dependency and Sample Efficiency	Interpretability and Explainability	Adaptability and Transferability	Ethical Considerations and Bias Mitigation	Cost and Implementation Feasibility	Resilience to Adversarial Attacks
Time-Series Forecasting Invalid source specified.	High performance in temporal pattern prediction with sufficient historical data, ensuring reliable demand forecasting.	Efficient for structured time-series data but computationally intensive for large datasets and deep learning models.	Heavily reliant on extensive historical data, with performance degrading when time-series continuity is disrupted.	High interpretability in traditional models like ARIMA, but reduced explainability in deep learning approaches such as LSTMs and transformers.	Limited adaptability to new datasets, with low transferability across domains, often requiring retraining for different time-series applications.	Less prone to societal biases but can reinforce historical data biases, potentially leading to inaccurate or unfair forecasting outcomes.	Implementation costs vary depending on data preprocessing and model complexity, with higher costs for deep learning-based forecasting.	Vulnerable to adversarial manipulation, as small perturbations in historical data can significantly impact future predictions.
Online Learning [51]	Accuracy depends on data stream quality and often requires adaptive algorithms to ensure consistency.	Efficient for real-time processing but depends on adaptive algorithms to handle complexity.	Efficiency relies on a continuous stream of high-quality data, but concept drift can diminish effectiveness over time.	Interpretability varies by algorithm, with adaptive models favoring performance over explainability.	Highly adaptive to dynamic environments but vulnerable to concept drift if data distribution changes are not properly managed.	Prone to bias if real-time data streams reinforce societal inequalities or propagate misinformation.	Cost-effective for continuous data streams but increases when adapting to concept drift.	Vulnerable to concept drift and adversarial influences in data streams.
Reinforce-ment Learning [52]	High accuracy in dynamic environments but reliant on reward design and exploration strategies.	Computationally demanding due to iterative exploration and reward optimization.	Requires extensive environmental interaction for learning, with low sample efficiency due to its trial-and-error approach.	Decision-making is difficult to explain due to complex reward structures and policy learning.	Highly adaptive in familiar settings but struggles with transferability unless reward functions and policies are aligned.	Biases can arise from reward structures, leading to ethically problematic behaviors if objectives are misaligned.	High implementation costs due to computational demands and environment simulation requirements.	Vulnerable to adversarial policies that exploit reward functions.

ML / Criteria	Ease of Implementation and Integration	Data Availability and Quality	Transparency	Operational Impact and Workflow Integration	Support and Maintenance	Risk Management and Data Privacy	Scalability and Futureproofing	User-Friendliness and Training Requirements
Time-Series Forecasting Invalid source specified.	Easily deployable for structured time-series data, but deep learning models require specialized expertise.	Highly dependent on extensive historical data, with performance declining when data is sparse or inconsistent.	Traditional models like ARIMA offer clear insights, but deep learning-based forecasting remains a black-box approach.	Seamlessly enhances demand forecasting and inventory planning but requires periodic model retraining for accuracy.	Needs continuous monitoring and updates, particularly in volatile markets where trends shift rapidly.	Sensitive to data privacy concerns, requiring robust encryption and access control for compliance.	Scales well with structured data, but deep learning models demand high computational resources for large-scale forecasting.	Traditional models are easy to interpret, but deep learning-based approaches require domain expertise and specialized training.
Online Learning [51]	Easy to integrate into real-time systems, though continuous adaptation complicates implementation when data quality fluctuates.	Continuous data availability remains essential. Model performance declines with noisy or outdated data streams.	Moderate transparency, though continuous adaptation complicates interpretation.	Moderate impact due to continuous model updates. Workflow integration requires real-time data pipelines and adaptive system designs.	Continuous maintenance required to manage real-time data streams and address concept drift.	High privacy risks due to continuous data processing. Risk management requires real-time monitoring and anomaly detection.	High scalability for real-time data streams, though concept drift increases resource demands.	Moderate user-friendliness, though real-time adaptation complicates deployment.
Reinforce-ment Learning [52]	Complex to implement due to iterative learning and environment simulations, but highly effective for optimizing dynamic decision-making processes.	Highly dependent on extensive interaction with the environment, with data quality reliant on accurate simulations and feedback loops.	Poor transparency due to complex policy learning and unpredictable environment interactions.	High operational impact, requiring infrastructure capable of real-time adaptation and continuous interaction with dynamic environments.	Demands frequent updates and policy refinements to maintain accuracy as environments evolve.	Moderate privacy risks when sensitive data is used in reward functions, but well-defined policies enhance security and regulatory compliance.	Highly scalable when trained on generalized policies, but performance depends on computational resources and adaptation to new environments.	Requires expertise in environment modeling and reward optimization, but once deployed, automates complex decision-making with minimal human intervention.

ML / Criteria	Ease of Implementation and Integration	Data Availability and Quality	Transparency	Operational Impact and Workflow Integration	Support and Maintenance	Risk Management and Data Privacy	Scalability and Futureproofing	User-Friendliness and Training Requirements
Time-Series Forecasting Invalid source specified.	Easily deployable for structured time-series data, but deep learning models require specialized expertise.	Highly dependent on extensive historical data, with performance declining when data is sparse or inconsistent.	Traditional models like ARIMA offer clear insights, but deep learning-based forecasting remains a black-box approach.	Seamlessly enhances demand forecasting and inventory planning but requires periodic model retraining for accuracy.	Needs continuous monitoring and updates, particularly in volatile markets where trends shift rapidly.	Sensitive to data privacy concerns, requiring robust encryption and access control for compliance.	Scales well with structured data, but deep learning models demand high computational resources for large-scale forecasting.	Traditional models are easy to interpret, but deep learning-based approaches require domain expertise and specialized training.
Online Learning [51]	Easy to integrate into real-time systems, though continuous adaptation complicates implementation when data quality fluctuates.	Continuous data availability remains essential. Model performance declines with noisy or outdated data streams.	Moderate transparency, though continuous adaptation complicates interpretation.	Moderate impact due to continuous model updates. Workflow integration requires real-time data pipelines and adaptive system designs.	Continuous maintenance required to manage real-time data streams and address concept drift.	High privacy risks due to continuous data processing. Risk management requires real-time monitoring and anomaly detection.	High scalability for real-time data streams, though concept drift increases resource demands.	Moderate user-friendliness, though real-time adaptation complicates deployment.
Reinforcement Learning [52]	Complex to implement due to iterative learning and environment simulations, but highly effective for optimizing dynamic decision-making processes.	Highly dependent on extensive interaction with the environment, with data quality reliant on accurate simulations and feedback loops.	Poor transparency due to complex policy learning and unpredictable environment interactions.	High operational impact, requiring infrastructure capable of real-time adaptation and continuous interaction with dynamic environments.	Demands frequent updates and policy refinements to maintain accuracy as environments evolve.	Moderate privacy risks when sensitive data is used in reward functions, but well-defined policies enhance security and regulatory compliance.	Highly scalable when trained on generalized policies, but performance depends on computational resources and adaptation to new environments.	Requires expertise in environment modeling and reward optimization, but once deployed, automates complex decision-making with minimal human intervention.

ML / Criteria	Ease of Implementation and Integration	Data Availability and Quality	Transparency	Operational Impact and Workflow Integration	Support and Maintenance	Risk Management and Data Privacy	Scalability and Futureproofing	User-Friendliness and Training Requirements
Time-Series Forecasting Invalid source specified.	Easily deployable for structured time-series data, but deep learning models require specialized expertise.	Highly dependent on extensive historical data, with performance declining when data is sparse or inconsistent.	Traditional models like ARIMA offer clear insights, but deep learning-based forecasting remains a black-box approach.	Seamlessly enhances demand forecasting and inventory planning but requires periodic model retraining for accuracy.	Needs continuous monitoring and updates, particularly in volatile markets where trends shift rapidly.	Sensitive to data privacy concerns, requiring robust encryption and access control for compliance.	Scales well with structured data, but deep learning models demand high computational resources for large-scale forecasting.	Traditional models are easy to interpret, but deep learning-based approaches require domain expertise and specialized training.
Online Learning [51]	Easy to integrate into real-time systems, though continuous adaptation complicates implementation when data quality fluctuates.	Continuous data availability remains essential. Model performance declines with noisy or outdated data streams.	Moderate transparency, though continuous adaptation complicates interpretation.	Moderate impact due to continuous model updates. Workflow integration requires real-time data pipelines and adaptive system designs.	Continuous maintenance required to manage real-time data streams and address concept drift.	High privacy risks due to continuous data processing. Risk management requires real-time monitoring and anomaly detection.	High scalability for real-time data streams, though concept drift increases resource demands.	Moderate user-friendliness, though real-time adaptation complicates deployment.
Reinforce-ment Learning [52]	Complex to implement due to iterative learning and environment simulations, but highly effective for optimizing dynamic decision-making processes.	Highly dependent on extensive interaction with the environment, with data quality reliant on accurate simulations and feedback loops.	Poor transparency due to complex policy learning and unpredictable environment interactions.	High operational impact, requiring infrastructure capable of real-time adaptation and continuous interaction with dynamic environments.	Demands frequent updates and policy refinements to maintain accuracy as environments evolve.	Moderate privacy risks when sensitive data is used in reward functions, but well-defined policies enhance security and regulatory compliance.	Highly scalable when trained on generalized policies, but performance depends on computational resources and adaptation to new environments.	Requires expertise in environment modeling and reward optimization, but once deployed, automates complex decision-making with minimal human intervention.

ML / Criteria	**Ease of Implementation and Integration**	**Data Availability and Quality**	**Transparency**	**Operational Impact and Workflow Integration**	**Support and Maintenance**	**Risk Management and Data Privacy**	**Scalability and Futureproofing**	**User-Friendliness and Training Requirements**
Time-Series Forecasting Invalid source specified.	Easily deployable for structured time-series data, but deep learning models require specialized expertise.	Highly dependent on extensive historical data, with performance declining when data is sparse or inconsistent.	Traditional models like ARIMA offer clear insights, but deep learning-based forecasting remains a black-box approach.	Seamlessly enhances demand forecasting and inventory planning but requires periodic model retraining for accuracy.	Needs continuous monitoring and updates, particularly in volatile markets where trends shift rapidly.	Sensitive to data privacy concerns, requiring robust encryption and access control for compliance.	Scales well with structured data, but deep learning models demand high computational resources for large-scale forecasting.	Traditional models are easy to interpret, but deep learning-based approaches require domain expertise and specialized training.
Online Learning [51]	Easy to integrate into real-time systems, though continuous adaptation complicates implementation when data quality fluctuates.	Continuous data availability remains essential. Model performance declines with noisy or outdated data streams.	Moderate transparency, though continuous adaptation complicates interpretation.	Moderate impact due to continuous model updates. Workflow integration requires real-time data pipelines and adaptive system designs.	Continuous maintenance required to manage real-time data streams and address concept drift.	High privacy risks due to continuous data processing. Risk management requires real-time monitoring and anomaly detection.	High scalability for real-time data streams, though concept drift increases resource demands.	Moderate user-friendliness, though real-time adaptation complicates deployment.
Reinforce-ment Learning [52]	Complex to implement due to iterative learning and environment simulations, but highly effective for optimizing dynamic decision-making processes.	Highly dependent on extensive interaction with the environment, with data quality reliant on accurate simulations and feedback loops.	Poor transparency due to complex policy learning and unpredictable environment interactions.	High operational impact, requiring infrastructure capable of real-time adaptation and continuous interaction with dynamic environments.	Demands frequent updates and policy refinements to maintain accuracy as environments evolve.	Moderate privacy risks when sensitive data is used in reward functions, but well-defined policies enhance security and regulatory compliance.	Highly scalable when trained on generalized policies, but performance depends on computational resources and adaptation to new environments.	Requires expertise in environment modeling and reward optimization, but once deployed, automates complex decision-making with minimal human intervention.

Learning a

Learning b

Learning c ot comparative analysis-a

F) Survey Structure

Survey Title: Survey on Identifying Processes in Logistics SMEs Suitable for Machine Learning Adoption

Introduction: Thank you for participating in this survey. Your insights are invaluable in helping us identify operational processes within logistics small and medium-sized enterprises (SMEs) that could benefit from the adoption of machine learning (ML) technologies. The findings from this survey will contribute to the development of a framework designed to support logistics SMEs in preparing for the integration of ML solutions to improve operational efficiency, decision-making and enhancing growth, while maintaining competitiveness and data privacy.

This survey will take approximately **10 minutes** to complete. Please note that your responses will remain anonymous and will be used exclusively for academic research purposes, adhering to GDPR and ethical research standards.

Section 1: Demographic and Organizational Background

Q1: What is your role in the organization?

- Owner/CEO
- Manager
- Operations Staff
- Other (please specify): __________

Q2: How many employees does your organization have?

- Fewer than 10
- 10–50
- 51–100
- More than 100

Q3: What types of logistics services does your company provide? (You may select multiple options.)

- Warehousing
- Inventory Management
- Transportation and Delivery
- Supply Chain Management

- Other (please specify): __________

Q4: How would you describe the primary focus of your company?

- Domestic Logistics
- International Logistics
- Both

Section 2: Current Operational Processes

Open Questions

Q5: What are the key daily processes in your organization? (e.g., inventory management, route optimization, scheduling, or supply chain tracking)

Q6: What challenges or inefficiencies do you commonly experience in your operations? (e.g., delays, high costs, inaccurate demand forecasting)

Q7: Are there any processes that require significant manual effort or are prone to errors? If yes, please describe.

Section 3: Process-Specific Challenges and Objectives

Q8: Are there processes where decision-making takes significant time or is prone to delays or errors?

Yes (please describe): __________

No

Q9: Are there processes in your company that involve handling large volumes of data? If yes, please specify.

Yes (please describe): __________

No

Q10: Would automating certain repetitive tasks improve productivity in your organization?

Yes (please specify which tasks): __________

No

Q11: Are there areas in your company where forecasting or planning improvements could reduce costs or enhance efficiency?

Yes (please describe): __________

No

Section 4: Awareness of and Willingness to Adopt Technological Solutions

Q12: Has your organization previously adopted any digital or technological tools to improve operations?

Yes (please specify which tools): __________

No

Q13: What are your main concerns regarding the adoption of new technologies in your company? (You may select multiple options.)

Cost

Complexity of implementation

Training and skill requirements

Potential data privacy issues

Lack of trust in new technologies

Other (please specify): __________

Q14: How do you envision technology improving your current operations? (e.g., faster decision-making, better forecasting, reduced costs)

Section 5: Final Open-Ended Questions

Q15: In your opinion, what areas of your company would benefit most from new tools or processes?

Q16: Do you have any additional comments or suggestions about your company's operations and challenges?

Thank you Note

Thank you for taking the time to complete this survey. Your input is highly valued and will directly contribute to the development of a framework aimed at supporting logistics SMEs in preparing for the adoption machine learning technologies to enhance their operations. If you are interested in receiving updates about the project, please let us know. The results of this study, presented in an aggregated and anonymous form, will help identify actionable strategies for ML adoption in logistics SMEs.

G) Interview Structure

Category 1: Data Readiness

Can you walk me through how your company usually gathers information about deliveries, inventory, or other daily logistics operations?

Do the people working in your company follow the same method every time they collect this kind of information?

Where is the information you collect usually stored—on paper, in spreadsheets, in software, or somewhere else?

If someone needs to look up past information about a shipment or delivery, how easy is it to find?

How often do you come across errors, missing details, or mismatched numbers in your company's logistics records?

When something goes wrong because of incorrect or missing information, what typically happens?

Do the systems or tools you use—for example, for managing transport, inventory, or customers - share information with each other automatically?

If information is entered into one system, do you have to manually enter it again somewhere else?

How far back can you look if you wanted to find information about orders, deliveries, or inventory from the past?

When planning upcoming deliveries or purchases, do you ever check how similar things were handled in previous months or years?

Category 2: System & IT Maturity

What kind of devices or systems do you use for managing operations - like computers, servers, or tablets?

Have you ever had a problem where your current systems were too slow or not strong enough to handle something you needed?

What kind of software do you use to keep track of orders, shipments, or stock?

Can this software connect easily with other programs, or are there limitations?

Who helps you when there is a problem with your computer systems or logistics software?

How quickly are technical problems usually solved when they happen?

Have there been situations where your systems needed updating or replacing to meet new needs?

How difficult is it for your company to switch to a new system or upgrade your current tools?

How reliable is your internet connection at your work locations, including warehouses or offices?

Have you had cases where a poor or unstable connection caused issues for your staff or systems?

Category 3: Organizational & Cultural Readiness

How involved is company leadership when new tools or systems are introduced?

Who usually makes the final decisions when there is talk about trying something new in how your logistics work is managed?

How comfortable are your employees with using computers or software in their daily tasks?

Have your employees received any training to help them work with new digital tools?

Can you describe how your company usually handles changes to work processes or tools?

Have past changes led to challenges or confusion among staff?

What do your employees usually think when a new tool or system is introduced—are they supportive, hesitant, or concerned?

Are your staff members ever asked for their opinion when the company is considering a new system?

Do the people responsible for IT in your company work closely with those handling daily logistics operations?

How often do teams from IT and logistics work together to solve problems or improve systems?

Category 4: Business Process Readiness

Are your logistics processes (such as deliveries or inventory checks) carried out in the same way by all employees?

Is there a clear guide or method that staff follow to ensure these processes are done consistently?

What parts of your logistics operations tend to take more time or lead to mistakes?

Are there specific tasks that your team regularly finds frustrating or inefficient?

Are there any tasks in your logistics process that happen automatically without someone doing them manually?

Which activities still require a lot of manual work, even though you think they could be done faster with a system?

When decisions are made (like restocking or scheduling deliveries) do you mostly rely on experience, or do you use data and reports?

What kinds of information are typically reviewed before making important logistics decisions?

Are there specific indicators or results that you regularly check to see how well your logistics operations are performing?

How often do you track things like delivery delays, stock levels, or customer satisfaction?

Category 5: Strategic Alignment

Are there specific problems in your logistics operations that you would like to solve using better tools or systems?

Have you ever thought about using technology to help with things like predicting demand or planning delivery routes?

Are you aware of what similar companies in your sector are doing to improve their logistics with digital tools?

Do you ever compare your logistics performance or systems with those of your competitors?

Has your company set aside a budget or financial plan for upgrading or improving digital systems?

How do you usually decide whether to invest in a new system or keep working with what you have?

Does your company have goals related to sustainability, like reducing emissions or cutting waste in logistics?

Have you looked for tools or systems that could help make your operations more environmentally friendly?

How do your logistics processes affect the experience of your customers - like delivery times or order tracking?

Have you ever considered improving your logistics operations to better meet customer expectations?

Category 6: Security & Regulatory Compliance

What kind of steps does your company take to keep sensitive information safe (such as customer addresses or delivery records)?

Are employees aware of any rules they should follow when handling personal or company data?

Does your company use things like firewalls, antivirus software, or secure passwords to protect its systems?

Have you ever experienced or worried about a security issue, such as being hacked or losing data?

Are you required to follow any specific rules or regulations when it comes to how your company handles data?

Has your company ever been checked by outside organizations to ensure it is following legal or industry rules?

Are there people in your company who are responsible for checking if your systems are secure and working properly?

What happens if a serious problem or mistake occurs with your digital systems?

Who in your company has access to important digital systems and how is that access managed? Do employees use passwords or other security steps to access your company's systems?

Category 7: External Dependencies & Ecosystem Readiness

Do the companies you work with (like software providers or delivery partners) use reliable and up-to-date digital systems?

Have you ever had problems with a vendor's system that affected your own operations?

How often do you hear about new tools or technologies being used in your industry to improve logistics?

Do you stay informed about changes in technology that might affect how your business runs?

Does your company ever use outside information—such as weather forecasts, fuel prices, or traffic data—to make logistics decisions?

If yes, where do you get this information and how do you use it?

Does your company have access to people—either internal or external—who understand how to work with advanced digital tools or AI?

Have you ever worked with consultants, freelancers, or IT companies for help with digital projects?

Has your company ever collaborated with a university, research group, or innovation program to improve your operations?

Would you be open to working with academic or research institutions in the future if it helped improve your logistics?

Category 8: Scalability & Long-Term Viability

If your business grows, can your current digital tools and systems handle more orders, deliveries, or customers?

Have you ever had to upgrade or change your systems because your current ones could not keep up?

Can your systems and software easily be adjusted, upgraded, or connected to new tools if needed?

Has it been easy or difficult for your company to adapt its systems when business needs change?

How do you usually track the cost of running your digital systems or logistics tools?

Have you looked for ways to reduce costs related to your software, hardware, or IT services?

Once a new digital system is in place, how do you make sure it stays up to date and keeps working well?

Who is responsible for keeping track of updates or improvements to your logistics systems?

Are there any rules, procedures, or responsible persons in your company that guide how digital tools are introduced and used?

When a new tool or system is being considered, who decides how it should be managed or used?

H) Prioritized Requirements

Business Requirements

Table 14 | Business Requirements

Identifier	Label	MSCW	Requirement
BR-01	ML Readiness Assessment	M	The framework must provide a structured assessment methodology to evaluate the current ML readiness of logistics SMEs.
BR-02	Strategic Implementation Guidance	M	The framework must offer SMEs a step-by-step roadmap for preparing their infrastructure, data, and workforce for ML adoption.
BR-03	Regulatory and Compliance Alignment	M	The framework should incorporate regulatory considerations and compliance requirements (e.g., GDPR) to ensure responsible ML adoption.

User Requirements

Legend:

NotIT User – Users that will utilize the applied framework for their purposes once it has been implemented into the companies.

IT User – Developer User (Developer users are people that will manage and update the framework, as well as the data readiness and governance of the companies.)

Table 15 | User Requirements

Identifier	Label	MSCW	Requirement
UR-01	Readiness Evaluation Tool	M	All users want the framework to provide an interactive assessment tool that evaluates ML readiness based on business processes, data, and infrastructure.
UR-02	Custom Recommendations	M	NonIT Users want the framework to provide recommendations based on their specific business needs and current ML readiness level.
UR-03	Actionable Insights	M	NonIT Users want the framework to display key readiness gaps and offering strategic next steps for ML adoption.
UR-04	Privacy and Security Guidelines	M	IT Users want the framework to include guidance on data privacy and security compliance, ensuring that ML adoption aligns with GDPR and other regulatory requirements.
UR-05	Cost Estimation Support	W	NonIT Users want the framework to offer an estimation of financial investments required for ML implementation, considering infrastructure, expertise, and software costs.
UR-06	Integration Feasibility Analysis	S	IT Users want the framework to evaluate the feasibility of integrating ML solutions into the existing company IT infrastructure.
UR-07	Industry-Specific Use Cases	C	All users want the framework to include real-world case studies that demonstrate successful ML applications in logistics SMEs.
UR-08	User-Friendliness	M	NonIT Users want the framework to provide intuitive guidance that does not require technical expertise for understanding it / applying it.
UR-09	Knowledge Hub	C	NonIT Users want the framework to provide an educational resource hub that explains ML concepts, business benefits, and best practices for implementation.
UR-10	Periodic Readiness Tracking	S	IT Users want the framework to allow companies to track their ML readiness progress over time and update their assessment periodically.

System (Framework) Functional Requirements

Table 16 | System Functional Requirements

Identifier	Label	MSCW	Requirement
FR-01	Readiness Assessment Methodology	M	The framework must define a structured methodology for assessing ML readiness across key areas such as data infrastructure, organizational preparedness, and business strategy.
FR-02	ML Implementation Roadmap	M	The framework must outline a step-by-step roadmap that logistics SMEs can follow to prepare for ML adoption based on their readiness level.
FR-03	Data Governance Guidelines	M	The framework must provide guidelines on data collection, quality assurance, security, and compliance to ensure SMEs can properly manage their ML-related data assets.
FR-04	Business Integration Strategy	M	The framework must provide SMEs with strategies for integrating ML into their existing business processes and identifying key areas where ML can provide value.
FR-05	Risk and Compliance Considerations	S	The framework must include an analysis of potential risks associated with ML adoption and provide recommendations for compliance with GDPR and other relevant regulations.
FR-06	Industry-Specific Best Practices	S	The framework should include best practices for ML adoption specific to logistics SMEs, considering sector-specific challenges and opportunities.
FR-07	Cost-Benefit Analysis Guidelines	S	The framework should provide methodologies for SMEs to assess the financial viability of ML adoption and estimate costs associated with infrastructure, training, and deployment.

FR-08	Change Management Recommendations	S	The framework should include guidelines on how SMEs can manage organizational changes and employee training as part of ML adoption.
FR-09	Continuous Improvement Strategy	S	The framework should provide a mechanism for SMEs to revisit and update their ML readiness strategy based on technological advancements and evolving business needs.
FR-10	SME Success Metrics	C	The framework could define key performance indicators (KPIs) that SMEs can use to measure the success of their ML adoption efforts.

System (Framework) Non-Functional Requirements

Table 17 | System Non-Functional Requirements

Identifier	Label	MSCW	Requirement
NFR-01	Accessibility	M	The framework must be written in clear, non-technical language to ensure usability for SMEs with limited ML expertise.
NFR-02	Structuring & Readability	M	The framework must be well-structured, with sections clearly delineated for assessment, strategy, and guidance.
NFR-03	Scalability	M	The framework must be adaptable for different company sizes, allowing SMEs at various stages of readiness to utilize its recommendations.
NFR-04	Compliance Agreement	M	The framework must align with industry standards and EU regulations regarding AI, data privacy, and digital transformation.
NFR-05	Evidence-Based Approach	M	The framework must be based on research, best practices, and real-world case studies to ensure its recommendations are practical and effective.
NFR-06	Updateability	S	The framework should be designed in a way that allows for periodic updates to reflect technological advancements and regulatory changes.
NFR-07	Implementation Flexibility	S	The framework should accommodate multiple ML adoption pathways, allowing SMEs to choose an approach that aligns with their business needs.
NFR-08	Modularity	S	The framework should be structured in a modular way, enabling SMEs to focus on specific readiness aspects independently.
NFR-09	Visual Aids & Examples	C	The framework could include visual aids such as flowcharts, readiness checklists, and case study summaries to improve comprehension.
NFR-10	Multi-Format Availability	C	The framework could be available in multiple formats, including PDF, web-based resources, and printed copies, to enhance accessibility

I) Detailed Guidance

Data Readiness – Data Collection

What is advised?

It is advised that logistics SMEs progressively replace user-entered data with automated collection mechanisms that capture operational events directly from systems, sensors, or structured interfaces. This includes transitioning to tools that log activities without manual effort, such as barcode scanners updating stock in WMS, telematics recording vehicle movements, or digital forms triggered by workflow actions. Systems should be selected or configured to collect data in real time or near-real time, ensuring that the captured records reflect actual events rather than manual approximations. This reduces input errors, improves traceability, and creates datasets suitable for ML development.

Why is it advised?

Manual data entry is error-prone, time-consuming, and difficult to scale. In logistics operations (where speed, volume, and coordination are critical) data reliability is essential for both operational performance and predictive modelling. Automating data capture increases consistency, reduces missing records, and allows events to be recorded as they happen. This leads to more trustworthy datasets, which are essential for building ML models that forecast demand, optimize routes, or flag anomalies. Without automation, ML efforts stall under the weight of data cleaning and ambiguity.

How to do it?

To initiate the transition toward automated data collection, the logistics SME must first examine how data is currently gathered across its operations. This includes reviewing all processes related to inventory movements, order processing, vehicle dispatch, loading and unloading, and delivery confirmation. Each of these points should be analyzed in terms of whether data is collected manually, semi-digitally, or automatically by an existing system. The focus should be placed on identifying the most frequent and error-prone manual entries, which are often the source of fragmented or delayed records.

Where manual entry is dominant, the SME should assess whether existing operational tools (such as ERP systems, warehouse management systems, or transport management systems) contain underutilized features that enable automatic logging. In many cases, these systems include native support for data capture through devices like barcode scanners, mobile apps, or system-triggered workflows, but these functionalities remain inactive due to lack of awareness or configuration. For example, a warehouse system may support barcode scanning for stock updates, yet staff may still enter such changes manually because the scanner function has not been set up or the process has not been standardized.

In the absence of suitable systems, SMEs should explore lightweight software solutions that offer built-in automation features. These may include mobile applications used by drivers to register delivery statuses, barcode-based inventory tools that feed directly into warehouse records, or telematics systems that continuously log vehicle positions and travel durations. These tools can often be deployed in modular form and integrated progressively with existing processes without disrupting the overall operational workflow.

It is essential that data automation is not only introduced but also aligned with existing logistical procedures. To do so, SMEs should document the key operational processes where system-based data collection could replace human entry. Wherever data is already passing through digital systems, SMEs should configure those systems to automatically record transitions and timestamps. For instance, when an order is marked as "packed" in an ERP system, that status change can trigger an automatic record update in a connected dispatch or invoicing module. Such configurations reduce the need for duplicate inputs and ensure event consistency across systems.

Moreover, attention should be given to maintaining consistent data formats and identifiers. As automation is introduced, the SME should ensure that records use standardized field names and values to facilitate reuse, aggregation, or future integration. Employees should be trained to interact with structured digital inputs rather than free-text entries, which reduces variance and error. Starting with one process, such as delivery confirmation, SMEs can gradually expand automation to cover more areas, while monitoring the completeness and accuracy of the data being captured automatically.

Data Readiness – Data Storage

What is advised?

It is advised that logistics SMEs consolidate all critical logistics data into a single, centralized digital system, whether that is an ERP, a logistics platform, or a dedicated database. This central environment should contain all operational records necessary for managing inventory, shipments, vehicle movements, and customer orders. Rather than relying on separate files, applications, or personal storage habits, all logistics data should be maintained in a system that offers persistent storage, internal consistency, and shared access across relevant functions.

Why is it advised?

When data is stored in scattered locations (such as paper binders, spreadsheets on local machines, individual cloud folders, or isolated software tools) it becomes increasingly difficult to track operations reliably, share information across departments, or build a trustworthy historical record. Fragmentation also introduces risk: records may be duplicated, lost, or misaligned between systems. For SMEs aiming to adopt data-driven practices or implement machine learning, such environments delay progress and raise the cost of data preparation. By contrast, storing logistics data in one centralized system simplifies record-keeping, ensures consistency across operations, and provides a stable foundation upon which analytical tools or predictive models can later be developed.

How to do it?

The transition begins with eliminating paper-based and device-specific storage practices. Historical data stored in physical documents, local spreadsheets, or USB drives must be digitized and uploaded to a shared environment. While moving from physical to digital is an important first step, simply uploading files to cloud folders does not resolve the deeper issue of data fragmentation.

The primary objective must be to consolidate all operational logistics data (ranging from inventory and orders to deliveries and invoices) into a single system. For SMEs that have not yet used enterprise software, this typically involves adopting an ERP system or a logistics-specific digital platform. The adoption of an ERP should be approached in structured, incremental stages.

The process begins with a clear inventory of current systems, tools, and storage practices. The SME must identify what data exists, where it resides, who maintains it, and how often it is used. This includes datasets for procurement, product movement, order fulfilment, vehicle dispatch, and customer invoicing. Once this landscape is understood, the SME must define which of these data domains will be centralized first, typically starting with order and inventory management.

When selecting an ERP, the SME should opt for a solution that is proportionate to its scale and operational complexity. Many lightweight, modular ERP systems exist that are cost-effective, easy to configure, and tailored to logistics workflows. Factors to consider include ease of deployment, user-friendliness, integration capabilities, and vendor support. It is often more practical to begin with a cloud-based ERP offering preconfigured modules for core logistics functions.

Once selected, the SME must prepare its existing data for migration. This involves aligning field names, cleaning values, standardizing formats, and ensuring that identifiers, such as order numbers or SKU codes, are consistent across all records. A data migration template provided by the ERP vendor is typically used to structure the data before import. If technical support is limited, external consultants can facilitate this process on a part-time basis.

During deployment, the ERP system should be introduced gradually. A pilot phase focusing on a single process, such as inventory management, allows staff to become familiar with system navigation and workflows. Once the initial module is functioning reliably, other domains, such as delivery tracking or customer invoicing, can be added. Throughout this process, staff training is essential to prevent misuse, ensure accurate data input, and encourage adoption.

As the ERP becomes embedded into the SME's daily operations, it replaces isolated tools and spreadsheets. Data that was once scattered becomes continuously recorded within a single environment. More importantly, the ERP begins to function as the system of record, ensuring that all departments operate with the same set of up-to-date information. This eliminates discrepancies, facilitates analysis, and provides a consistent basis for integrating further digital tools or ML applications in the future.

Data Readiness – Data Consistency & Quality

What is advised?

It is advised that logistics SMEs adopt simple, automated routines that check for inconsistencies, anomalies, and missing entries in their operational datasets. These routines should be applied during or shortly after data entry to ensure that logistics records, such as delivery times, inventory quantities, or routing events, remain reliable and suitable for decision support and ML development. By establishing consistent validation steps, SMEs avoid polluting their data with avoidable errors and increase the usability of their datasets.

Why is it advised?

Machine learning relies on data that is not only available but also statistically and structurally reliable. If records contain irregularities—such as negative delivery durations, implausible stock levels, or undefined categories, then ML models learn from noise, leading to inaccurate predictions and reduced trust in system outputs. Moreover, poor data quality increases manual cleaning costs and delays project timelines. Consistent and high-quality data reduces rework, strengthens reporting, and improves model performance. Implementing basic validation early, even in small systems, protects the long-term value of digital records and supports scalable ML development.

How to do it?

The SME should start by identifying the most critical logistics datasets - typically delivery logs, inventory flows, and order data. For each dataset, they should define acceptable ranges and formats for key fields. Examples include:

- Delivery durations must be positive and below a realistic threshold (e.g., < 48 hours)
- Inventory entries must be numeric and non-negative
- Dates must follow a consistent format (e.g., YYYY-MM-DD)

Once defined, these rules can be encoded (using formulas or data validation), through no-code platforms, or as simple Python scripts applied to exported files. Many logistics tools already support validation templates or flags for missing or incorrect entries. The SME should activate these functions and ensure staff are aware of how to resolve flagged records.

Missing values should be identified routinely and resolved through correction, interpolation, or exclusion, depending on their frequency and context. Outlier detection can be done through conditional highlighting, threshold rules, or basic visual inspection (e.g., plotting values over time).

For small organizations without technical capacity, external support (e.g., data consultants or AI students) can be engaged to help design lightweight validation routines. These should be documented and run on a fixed schedule - weekly or monthly depending on data volume. SMEs should also maintain a log of detected and corrected issues to monitor progress over time and understand recurring problems in data entry or system configuration. This feedback loop improves not only data but also operational discipline.

Data Readiness – Data Integration

What is advised?

It is advised that logistics SMEs ensure their operational systems (such as order management, inventory tracking, transport planning, and warehouse control) can exchange and interpret data consistently. This involves aligning data fields across tools, creating standard relationships between datasets (e.g., linking orders with deliveries, or inventory with dispatch), and enabling automatic or semi-automatic communication between systems. Integration should prioritize continuity of information, avoiding disjointed datasets or repeated manual data transfers.

Why is it advised?

Most logistics SMEs rely on multiple software tools and processes, often acquired or implemented at different times. Without integration, each system holds only partial information, resulting in duplicated effort, errors, and misaligned operations. For example, if warehouse data is not linked to transport systems, delays or misloads may go unnoticed. Data integration allows systems to "talk" to each other, ensuring that updates in one area are reflected in others. For ML applications, this connectedness is essential: predictions require inputs from across the business, and model outputs must be reintroduced into workflows without friction. Integration therefore ensures consistency, reduces data silos, and creates a foundation for automation and analytics.

How to do it?

The SME should begin by identifying which systems hold related logistics data, such as delivery tracking software, ERP modules, inventory spreadsheets, or third-party tools. Next, the SME should map which data points are logically connected across systems (e.g., order ID, product code, time stamps) and assess whether these identifiers are aligned. Where formats or field names differ, a data dictionary can be created to document equivalencies.

Efforts should then be made to establish relationships between systems. This can be done through shared IDs, structured exports, or middleware solutions that match and reconcile records. For example, if order data from the ERP must be linked to routing decisions in a TMS, both systems should refer to a common reference, such as a shipment code or client number.

If systems cannot yet exchange data automatically, structured exports and manual imports can still be coordinated, provided field formats are aligned and naming is consistent. Over time, SMEs can evolve from periodic syncing to live or near-real-time exchange using connectors, scripts, or integration services.

Internal workflows should also be adjusted to ensure that new data, such as order changes or delivery updates, follows the same integration structure, avoiding fragmentation. If possible, SMEs should prefer software solutions that support structured imports/exports or allow for simplified field mapping during data exchange.

Data Readiness – Historical Data Availability

What is advised?

It is advised that logistics SMEs consolidate and structure their historical logistics data, such as delivery records, order fulfilment logs, stock movements, and routing outcomes into clean, consistently formatted datasets. This data should be stored in a retrievable and analyzable manner, allowing it to serve as a foundation for both operational insights and machine learning applications. Structuring past data is often more immediately achievable than real-time data engineering and remains one of the most valuable assets for initiating ML development.

Why is it advised?

Historical data forms the baseline for training predictive models, identifying operational patterns, and evaluating performance trends. In the logistics sector, past behaviors such as delays, load volumes, and dispatch outcomes, often serve as the most accurate predictor of future conditions. However, if the data is unstructured, scattered, or inconsistently recorded, it becomes unusable for ML purposes and costly to clean retroactively. By preparing structured historical datasets in advance, SMEs reduce future effort, accelerate ML development, and improve model reliability. Additionally, historical data enables diagnostic analyses that inform the prioritization of use cases and the understanding of process inefficiencies.

How to do it?

The SME should start by identifying which types of historical data are available and where they are stored. These may include spreadsheets, ERP exports, manual logs, or records from third-party systems (e.g., telematics or courier dashboards). The goal is to bring this data into a centralized and analyzable format, such as a cleaned Excel file or simple relational database.

During this process, consistency must be prioritized. Column names, data types, date formats, and units of measurement should be standardized. Duplicates, gaps, or inconsistent entries must be resolved where possible. For instance, delivery dates should follow one format, route names should be uniformly recorded, and status codes (e.g., "delivered", "DEL", "OK") should be consolidated. Even partial cleaning can yield significant gains in usability.

If datasets come from multiple sources, a mapping exercise may be required to align fields and definitions. SMEs may involve external data support (e.g., freelance analysts or academic partners) for initial cleaning if internal capacity is limited.

Once structured, the historical datasets should be stored in a secure and accessible repository - cloud folders, internal databases, or integrated ERP modules. The SME should document data coverage (e.g., “Delivery logs from Jan 2020 – Jan 2024"), known quality issues, and which systems generated which datasets. This documentation is key to enabling effective reuse and ensuring future ML efforts build on the right foundations.

System & IT Maturity – Computational Readiness

What is advised?

It is advised that logistics SMEs establish computing capabilities—either in-house or cloud-based—that are technically suited to core ML operations. These capabilities must support basic computational tasks, including data cleaning, model training, inference generation, and visualization. Additionally, SMEs should plan their ML activities with respect to the known limitations of their existing infrastructure to avoid overloading critical systems or introducing avoidable delays.

Why is it advised?

Unlike static digital tools, machine learning involves iterative processing, often requiring increased memory, computation, and storage—even at a small scale. Insufficient computational readiness leads to crashes, long runtimes, or reduced experimentation speed, which discourages adoption. When computing is thoughtfully matched to ML task complexity, SMEs can develop, test, and deploy ML models without disrupting daily operations. This not only facilitates the launch of pilot use cases but also supports responsible resource use, cost management, and sustainable system performance.

How to do it?

The SME should begin by assessing the typical computational demands of its planned ML use cases. Lightweight tasks such as classification, clustering, or basic regression can often be run on modern laptops or mid-tier desktops, while resource-intensive tasks (e.g., time-series forecasting, deep learning) may require cloud computing or local servers with higher RAM or GPU support. Based on this, the SME must identify whether available machines are sufficient or if external options are needed.

For many SMEs, the most accessible path is to use cloud computing platforms (e.g., Google Colab, Microsoft Azure, AWS SageMaker) with free or low-cost tiers. These platforms enable SMEs to test and train models without investing in high-spec machines. When selecting a platform, the SME should consider ease of use, available support, and compatibility with the tools being used (e.g., Python environments, Jupyter notebooks, data pipeline tools).

Internally, SMEs should catalogue available computing assets—documenting specifications such as RAM, storage, processor type, and operating system. Where gaps are found, reallocation of underused devices or upgrades to RAM and disk capacity may provide temporary solutions.

ML-related tasks should be scheduled to avoid overloading operational systems. For instance, batch model training can be performed outside working hours or on isolated devices. SMEs should also introduce simple protocols for data file organisation, local backup, and result tracking to avoid computational redundancy and improve reproducibility.

As capabilities grow, basic performance monitoring should be introduced to track runtimes, model performance speed, and hardware usage. This can inform future decisions about when to invest in better equipment or transition more tasks to scalable cloud environments.

System & IT Maturity – Logistics Software & ML Compatibility

What is advised?

It is advised that logistics SMEs evaluate and adapt their core software platforms—such as ERP, WMS, or TMS—so that they can supply structured, accessible data and expose integration points (e.g., APIs, export functions) suitable for use in ML projects. The goal is to ensure that logistics data can be extracted cleanly and regularly, without excessive manual reformatting, and that ML models can later interact with these systems if needed.

Why is it advised?

Machine learning cannot be meaningfully applied without access to structured data. If logistics systems produce inconsistent outputs, or if exports are locked behind proprietary tools or non-standard formats, the cost of preparing data for ML becomes prohibitively high. Similarly, without API access or integration capabilities, ML models remain siloed and disconnected from the processes they are meant to improve. Ensuring software compatibility allows SMEs to generate useful training data, validate use cases, and eventually incorporate model outputs into planning or decision workflows. This also future-proofs digital investments by enabling experimentation without requiring wholesale system replacement.

How to do it?

The SME should begin by assessing whether its current logistics systems support structured exports—such as CSV, JSON, or database dumps—and whether these exports contain time stamps, unique identifiers, and cleanly labelled fields. If data is locked into unstructured formats (e.g., PDF, Word), conversion routines must be developed or manual effort allocated to reformat critical datasets.

Next, the SME should determine whether the system allows access through APIs or batch export features. If no such functionality exists, the SME should contact the software vendor to request export or integration options. For in-house or open-source tools, lightweight scripts (e.g., using Python or Power Query) may be written to automate data retrieval.

Basic API knowledge is useful but not essential; SMEs can work with IT providers or local partners to test whether data can be periodically pulled or pushed between systems. It is often sufficient at this stage to set up a working data pipeline that delivers clean input to a Jupyter notebook or ML dashboard.

When purchasing or renewing software contracts, the SME should include ML compatibility criteria in vendor selection—such as export structure, schema documentation, or integration with analytics environments. Investing in platforms that support external ML workflows will reduce friction and prevent long-term dependency on closed systems.

System & IT Maturity – IT Maintenance & Support

What is advised?

It is advised that logistics SMEs maintain a reliable IT maintenance function—either through internal staff or external service providers—that ensures the consistent performance, update management, and issue resolution of all critical IT systems. This includes monitoring hardware, operating systems, software tools, and infrastructure dependencies that underlie both routine logistics operations and more advanced digital tools. Maintenance must be proactive, scheduled, and traceable to avoid operational disruption and digital degradation over time.

Why is it advised?

Without structured IT maintenance, SMEs face growing risks of system failure, outdated software vulnerabilities, and performance bottlenecks that can disrupt daily logistics operations. In environments increasingly dependent on digital tools—such as warehouse scanners, ERP systems, transport dashboards, and cloud platforms—technical faults directly translate into delivery delays, miscommunication, or data loss. Additionally, ML readiness relies on dependable infrastructure: data cannot be captured, processed, or stored securely if the systems supporting those processes are unstable. Proactive IT support ensures that digital tools remain operational, scalable, and safe across the SME's growth trajectory.

How to do it?

The SME should begin by assigning clear IT support responsibility. This can be fulfilled internally (e.g., by a staff member with basic IT competence) or externally (e.g., via an IT services company or managed IT provider). The key requirement is that someone is accountable for maintaining digital system health on an ongoing basis—not only in emergency situations.

Next, the SME should establish a basic IT maintenance plan. This should include routines for:

- System updates (e.g., operating systems, business software, firmware)
- Hardware health checks (e.g., backup devices, workstations, routers)
- Security patching and antivirus monitoring
- User account and permission reviews
- Scheduled backups and recovery tests

These routines should be documented in a short checklist and scheduled at regular intervals (monthly, quarterly, or semi-annually depending on system complexity). SMEs can use automated alerts, calendar reminders, or service-level agreements (SLAs) to ensure these tasks are completed consistently.

For troubleshooting, SMEs should maintain a simple issue tracking log, recording system failures, response times, and resolution steps. Over time, this supports better planning, vendor selection, and identification of recurring issues.

Lastly, SMEs should establish basic escalation procedures: when and how to contact external support, what recovery procedures to follow for critical systems, and how to inform staff if access is interrupted. These processes improve resilience and minimize productivity loss during technical downtime.

System & IT Maturity – IT Adaptability & Future Readiness

What is advised?

It is advised that logistics SMEs develop a structured IT roadmap that outlines how current systems will evolve to accommodate future business and technological demands, including ML integration. This roadmap should identify risks of obsolescence, prioritise regular system updates, and signal key infrastructure milestones (e.g., hardware refresh, software phase-out, cloud migration). In parallel, the SME should actively monitor technological developments relevant to logistics and AI to ensure timely strategic adjustments. Awareness alone is insufficient—planned adaptability must be embedded into the SME's digital evolution.

Why is it advised?

IT systems that are static or outdated can quickly become a bottleneck to innovation. When core platforms are unsupported, lack interoperability, or no longer meet performance needs, integrating ML becomes complex, costly, or entirely infeasible. Furthermore, software that cannot evolve risks compatibility issues, security vulnerabilities, and operational inefficiencies. By anticipating infrastructure needs and adapting progressively, SMEs can preserve system continuity, reduce reactive spending, and remain aligned with digital developments in their sector. This strategic readiness ensures ML initiatives do not rely on fragile or obsolete foundations.

How to do it?

The SME should begin by auditing current infrastructure across software, hardware, and data systems. This audit should document the age of each system, last update, vendor support status, and known performance or compatibility limitations. Where systems are nearing end-of-life or have restricted scalability, they should be flagged for prioritised upgrading.

Next, the SME should define a simple, time-bound IT roadmap, ideally spanning two to three years. This document should identify:

- Key systems to upgrade or replace
- Planned investments in cloud services or hardware
- Target milestones for integration capacity (e.g., enabling APIs, ML inference support)
- Responsible roles and review intervals

The roadmap does not need to be complex; a one-page visual timeline or spreadsheet is sufficient if actively reviewed and maintained. Internal roles must be clearly assigned for implementation oversight and vendor coordination.

In parallel, the SME should establish a routine for monitoring technology trends relevant to logistics and AI. This could involve subscribing to newsletters from trusted industry bodies, attending one event per year (even virtually), or maintaining a shared document to collect observations about competitors or technologies under trial. The goal is not to adopt every trend, but to recognise signals that current systems may become insufficient.

To avoid obsolescence, SMEs should also formalize their software and hardware update policies. For instance, applications older than five years or unsupported by vendors should be reviewed for replacement. IT providers or external consultants may assist in assessing upgrade urgency and aligning replacements with the roadmap.

System & IT Maturity – Digital Connectivity & Network Maturity

What is advised?

It is advised that logistics SMEs invest in a stable and scalable digital network infrastructure that ensures uninterrupted connectivity for enterprise systems (e.g., ERP), cloud platforms, and real-time data exchange. This includes strengthening internal network architecture, securing reliable external internet access, and ensuring that network capacity is sufficient to support digital operations—especially as ML tools and data-heavy systems are introduced.

Why is it advised?

Reliable and high-performing network infrastructure is a prerequisite for any digital solution to function effectively. In logistics environments, even minor network instability can disrupt order processing, tracking, route coordination, and warehouse automation. As cloud platforms, ML models, and interconnected systems become integral to operations, downtime and latency become costlier and harder to absorb. A mature network supports real-time synchronization, data transfer to cloud services, API integrations, and remote access—ensuring digital continuity, scalability, and responsiveness across logistics workflows. Without this foundation, even the most advanced digital or ML systems fail to deliver consistent value.

How to do it?

The SME should begin by reviewing the current state of its network infrastructure. This includes examining local area network (LAN) setups within warehouses or offices, wide area network (WAN) connections across sites, and internet service quality. Common issues such as slow upload speeds, dropped connections, or dead zones within facilities should be identified and prioritized.

If ERP systems, cloud storage, or logistics platforms are hosted externally, the SME should confirm that network speeds and stability are sufficient to maintain uninterrupted synchronization. A practical step is to run periodic speed tests and latency checks, especially during peak operating hours. If bottlenecks or high variability are observed, switching to a business-grade internet service, increasing bandwidth, or segmenting traffic through network quality-of-service (QoS) settings may be necessary.

For internal networks, structured cabling, managed switches, and business-grade routers are recommended to minimize downtime and support future scaling. In sites with mobile operations (e.g., forklift terminals, handheld scanners), wireless coverage should be mapped and extended using mesh networking or industrial access points if needed.

To ensure fault tolerance, SMEs may consider backup internet connections (e.g., 4G/5G failover routers) in critical sites, particularly if cloud ERP or ML systems are involved. For businesses spread across multiple locations, virtual private networks (VPNs) or dedicated private links can improve reliability and security of inter-site data transfer.

Documentation is also critical. Network maps, IP address assignments, and configuration settings should be recorded and periodically updated to simplify troubleshooting and support scalability.

Organizational & Cultural Readiness – Leadership Buy-In

What is advised?

It is advised that leadership in logistics SMEs proactively endorses the adoption of machine learning by clearly articulating its strategic value and dedicating tangible resources to support its deployment. These resources may include budget allocation for exploratory ML initiatives, assignment of internal personnel to relevant roles, or the outsourcing of expertise to initiate small-scale pilot projects. Leadership must also communicate commitment by embedding ML into the company's innovation strategy or digitalization roadmap.

Why is it advised?

Leadership support serves as a decisive enabler for any transformation initiative. In the context of machine learning, the absence of leadership buy-in often results in fragmented experimentation, limited learning transfer, and a lack of sustained investment. Conversely, when leadership actively champions ML, the organization gains legitimacy to explore, fail, learn, and eventually integrate ML capabilities into operational workflows. For logistics SMEs with constrained resources, clear leadership direction ensures that limited budgets are invested strategically and that internal efforts remain aligned with measurable outcomes.

How to do it?

Leadership should begin by developing a fundamental understanding of what ML can offer within the logistics domain—such as optimizing delivery routes, forecasting demand, or automating warehouse operations. This can be accomplished by attending sector-specific webinars, reading case studies from similarly sized firms, or consulting with applied research institutions.

Once foundational understanding is gained, leaders should initiate a resource-light but focused pilot project. For instance, allocating one operational staff member to collaborate with an external consultant to prototype a basic ML model using historical logistics data. Simultaneously, a modest budget should be set aside for experimentation and external support.

To formalize commitment, leadership may publicly designate ML as a priority in company meetings, reports, or internal newsletters. Establishing a cross-functional team—however small—can further signal seriousness, especially if responsibilities include identifying promising use cases or assessing pilot results. Ultimately, even in SMEs, visible resource commitment combined with sustained interest from leadership cultivates an organizational environment where ML exploration is not seen as a luxury but as a necessity.

Organizational & Cultural Readiness – Workforce Digital Skills

What is advised?

It is advised that logistics SMEs ensure that employees across departments receive practical training in the use of core digital tools relevant to their roles, such as spreadsheets, transport planning software, or inventory management systems. In parallel, key personnel—such as operations managers, planners, and department heads—should be introduced to the principles of data-driven decision-making. This includes basic data interpretation, an understanding of what constitutes high-quality data, and how insights derived from data can inform operational improvements.

Why is it advised?

Machine learning solutions depend not only on technical deployment but also on human capacity to interface with digital systems and act upon data insights. For SMEs, upskilling the workforce reduces resistance to technological change and creates a stable foundation for more advanced digital applications, including ML. When staff understand and trust digital tools, data collection becomes more consistent, and decision-making more objective. Moreover, digitally capable personnel are better positioned to support, evaluate, and operationalize ML projects, ensuring smoother integration into daily operations and reducing reliance on external expertise.

How to do it?

Leadership should begin by identifying common digital tools already in use and assessing current staff proficiency. Based on this, a basic digital upskilling plan can be developed. This plan may include short internal workshops, free online courses (e.g., on Excel data functions, cloud-based logistics platforms), or mentorship from digitally proficient colleagues.

Key personnel should receive more targeted training in understanding KPIs, dashboards, and basic data analysis. For example, operations supervisors may learn how to interpret average delivery time trends and how such metrics can be used to adjust scheduling or route allocation. External trainers from applied research partners, vocational training centers, or software vendors can be brought in for brief, practice-oriented sessions tailored to SME operations.

It is not necessary to implement company-wide transformation at once. Instead, a focused effort on one department or process can serve as a pilot to demonstrate the benefits of digital literacy. Celebrating quick wins—such as identifying cost savings through spreadsheet analysis—can help build momentum and internal motivation for continued learning.

Organizational & Cultural Readiness – Change Management

What is advised?

It is advised that logistics SMEs develop a basic but structured change management plan that outlines the intended transition towards ML-supported workflows. The plan should address the objectives of the change, the steps required to reach them, roles and responsibilities, communication strategies, and potential sources of resistance. Even a short, clearly structured document is sufficient, provided it demonstrates forethought and coordination. The plan should be shared with relevant personnel and updated as the ML adoption process progresses.

Why is it advised?

Machine learning adoption, even when incremental, introduces new processes, technologies, and expectations that can disrupt established routines. Without a change management strategy, SMEs risk encountering low employee engagement, workflow confusion, or passive resistance—especially when resources and time are already limited. A structured plan reduces uncertainty, aligns internal expectations, and provides a stepwise guide for navigating the transition. Moreover, in SMEs where direct communication is frequent but often informal, documenting the change process ensures continuity even when responsibilities shift or staff turnover occurs.

How to do it?

A change management plan can be created using a basic template or editable document. It should begin by clearly stating the motivation for ML integration, for example, improving delivery route efficiency or automating demand forecasting. This should be followed by a phased roadmap, a template with basic guidelines presented in Figure 2, with approximate timelines, starting with preparation (e.g., data collection or pilot project planning), then small-scale testing, and eventually integration into regular operations.

In assigning roles, the plan should specify who is responsible for each phase—such as an IT-savvy employee overseeing data preparation or a logistics planner coordinating with external partners. Communication should be planned deliberately: short team meetings, periodic email updates, or a shared internal document that can be used to inform staff, invite feedback, and report on progress.

Critically, the plan should anticipate potential resistance. Staff may worry about job displacement, feel uncertain about using new tools, or doubt the usefulness of ML. Addressing these concerns upfront—with transparent communication, reassurances about job security, and training opportunities—can foster a more open and cooperative environment.

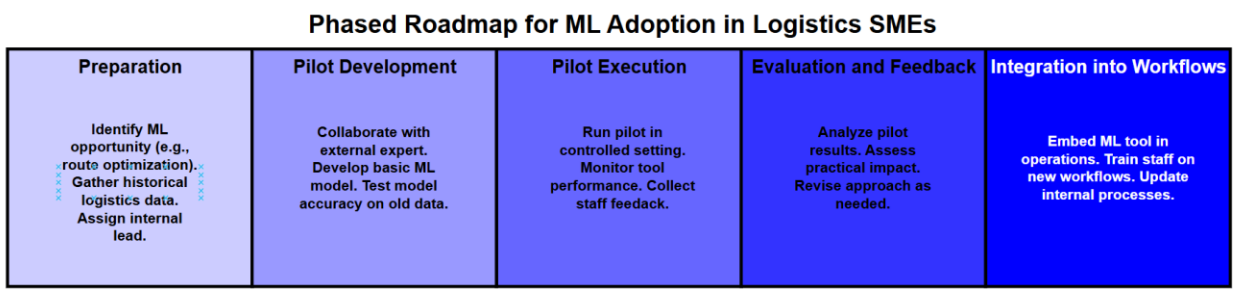

Figure 6 | Change Management Phased Roadmap Guidelines

Organizational & Cultural Readiness – Employees' Opinion

What is advised?

It is advised that logistics SMEs foster a participatory environment in which employees are encouraged and enabled to propose ideas for ML-supported improvements. Staff should not only feel permitted to voice suggestions but also be involved in shaping pilot initiatives or supporting implementation tasks, particularly where domain knowledge is essential. Structured channels for suggestion collection, combined with informal support mechanisms, should be introduced to transform employee insight into actionable input.

Why is it advised?

In logistics SMEs, operational staff possess intimate, experience-based understanding of where inefficiencies and delays occur. Such proximity to daily workflows enables them to identify promising areas for automation or predictive modeling, especially in functions like dispatching, warehousing, or fleet coordination. Moreover, when employees see their input reflected in implementation, their engagement deepens, and resistance diminishes. Given that ML initiatives often require on-the-ground feedback and domain-specific judgment, involving staff not only democratizes innovation but increases its practical relevance and success rate.

How to do it?

Management should first normalize the conversation around ML by introducing it in internal meetings, highlighting its role not as a job replacement but as a decision-support tool. Concrete examples from the logistics sector—such as forecasting delays or identifying maintenance needs—should be shared using plain language. This builds familiarity and reduces uncertainty.

To capture employee input, simple mechanisms such as monthly suggestion forms, shared whiteboards in break areas, or a digital feedback form on internal platforms can be used. Importantly, these should include guiding prompts to help staff formulate relevant ideas (e.g., "What is one task that feels repetitive or hard to predict?"). In some SMEs, morning stand-up meetings may be repurposed weekly to include a 5-minute discussion on workflow challenges or improvement opportunities, with one person designated to take notes and consolidate suggestions.

Once suggestions are gathered, leadership should select one low-risk proposal and develop it as a mini-pilot. Employees who proposed the idea should be invited to participate in the testing phase—whether that means validating outputs, reviewing system recommendations, or helping with data entry. Providing short training on the tools being used or holding a dedicated walkthrough session enhances their ability to contribute meaningfully.

As implementation progresses, visual recognition—such as highlighting contributors during internal updates or creating a small incentive (e.g., gift card or team lunch)—reinforces a culture where initiative is appreciated and rewarded. Over time, this builds a feedback loop where employees feel their opinions lead to real outcomes and thus continue to engage proactively.

Organizational & Cultural Readiness – IT-Operations Collaboration

What is advised?

It is advised that logistics SMEs actively facilitate structured collaboration between technical personnel (either internal or external) and operations staff. This collaboration should be grounded in mutual learning, clear task alignment, and shared ownership of the ML implementation process. Joint involvement in problem formulation, data exploration, and pilot validation ensures that ML solutions are tailored to the operational realities of logistics workflows rather than abstract technological possibilities.

Why is it advised?

ML initiatives frequently fail in SMEs not due to technical shortcomings but because of a disconnect between those who build the tools and those who use them. In logistics operations, where processes are dynamic and rarely standardized across firms, technical solutions must align precisely with the context in which they are deployed. Active collaboration bridges the gap between algorithmic thinking and logistical pragmatism. It also ensures that solutions address real bottlenecks, capture domain-specific nuance, and are adopted more readily by end-users.

How to do it?

The first step is identifying one or two technically proficient individuals who can serve as IT facilitators—this may be a part-time IT staff member, a technically trained logistics coordinator, or an external partner such as a university contact or freelance data scientist. Simultaneously, a small operational team should be appointed based on their process knowledge and communication readiness. This group might include a warehouse supervisor, a route planner, or a fleet manager.

To structure collaboration, define a joint ML task early in the process, preferably tied to a concrete issue (e.g., high variability in delivery durations, inaccurate inventory forecasts). Begin with a short kickoff session, where operational staff describe how the problem manifests and IT representatives translate this into technical terms—such as identifying what data is needed, how it will be processed, and what outputs would be actionable.

Regular touchpoints should be scheduled—ideally every one or two weeks—to review progress, adjust data interpretations, and ensure that technical developments match operational logic. These meetings should follow a short, repeatable format: updates on findings, clarification of logistics constraints, and a shared review of model performance or prototypes. Collaboration should also extend to interpreting early outputs; for instance, if a predictive model identifies patterns in shipment delays, operational staff should be asked to verify whether the insights align with their lived experience.

Documentation must be minimal but structured. A shared spreadsheet or a simple task board (e.g., Trello, Notion) can track what data has been shared, what assumptions are being made, and who needs to approve each implementation step. If technical literacy gaps arise, IT staff should offer brief, context-specific explanations rather than general training—such as showing how a dashboard works using real operational examples.

Business Process Readiness – Process Standardization

What is advised?

It is advised that logistics SMEs actively formalize their core operational processes by creating simplified, written descriptions of how routine tasks are carried out—such as order picking, dispatch scheduling, return handling, or freight tracking. These descriptions should reflect actual practices, not idealized workflows, and must be communicated to all employees involved. Clear, accessible documentation and shared understanding of procedures are prerequisites for introducing machine learning, which relies on repeatable patterns and clean data derived from consistent execution.

Why is it advised?

ML models function by identifying stable relationships between inputs and outcomes. When daily operations are executed in varying ways by different staff members or across shifts, the resulting data becomes noisy and unreliable, reducing model performance and complicating adoption. For logistics SMEs, where informal know-how often drives efficiency, this variability creates challenges in digitization. Standardization reduces operational ambiguity, ensures data consistency, and lays the groundwork for automation or prediction. Moreover, SMEs with documented processes gain agility, as new staff can be trained faster, and workflows can be improved iteratively.

How to do it?

The first step is to prioritize which processes to document. Focus should be placed on those with direct data relevance or high operational frequency—such as booking incoming goods, scheduling deliveries, or scanning inventory. A short internal meeting should be held with key employees to collectively map the steps of the selected process. This mapping must reflect actual behaviour, including informal shortcuts or deviations, in order to be accurate and meaningful.

Documentation can be created in the form of step-by-step checklists, annotated flowcharts, or illustrated guides. The tools used should be accessible and editable—such as Google Docs, Word templates, or physical boards in warehouses. Each document should state the purpose of the process, list the sequential actions, identify who is responsible at each step, and specify which data entries are required.

Once created, documentation should be circulated to all staff involved in the process. A short training session—ideally integrated into existing meetings or shift handovers—should be used to explain the content, address doubts, and gather feedback. Implementation should include spot-checks or short observations to confirm whether processes are being followed uniformly. Where divergence occurs, revisions should be made collaboratively to ensure the standard is both practical and respected.

To reinforce consistency, supervisors or team leads should be empowered to answer questions about process adherence and to update the documents when changes are made. In small teams, placing printed guides near workstations, or incorporating visual cues (e.g., stickers, printed labels) into the physical environment can help maintain routine execution without formal policing.

Business Process Readiness – Operational Inefficiencies

What is advised?

It is advised that logistics SMEs establish procedures for identifying and resolving operational inefficiencies directly within the structure of their standardized workflows. These procedures should facilitate quick diagnosis, clarify staff responsibilities, and formalize how corrective actions are to be implemented. The focus is not on introducing new technologies, but on embedding a mindset of continuous improvement into existing logistical routines.

If the processes within the logistics-focused SME are still not standardized into workflows or other formats, refer to the guidance of the previous concept – Process Standardization.

Why is it advised?

Although inefficiencies are common across all logistics operations, they often remain unaddressed in SMEs due to time constraints, limited managerial capacity, or reliance on tacit knowledge. Yet these inefficiencies—such as duplicated handling steps, uncoordinated dispatching, or inventory mismatches—significantly compromise workflow stability. This variability distorts operational data and impairs the usefulness of any subsequent machine learning deployment. Integrating structured problem-solving into workflows ensures that inefficiencies are surfaced early, resolved consistently, and prevented from recurring without relying on informal escalation or reactive firefighting.

How to do it?

Building on previously standardized processes, SMEs should define what constitutes a deviation from expected execution. These deviations must be framed in operational terms that staff can quickly recognize—such as missing documentation during goods receipt, repeated manual corrections in stock counts, or customer complaints due to inaccurate delivery times.

For each identified inefficiency-prone area, a set of structured response steps should be embedded into the workflow. For example, in a dispatch workflow, if a route change is required due to vehicle unavailability, a fallback protocol (such as predefined reallocation rules or supervisor override) should be part of the documented process. The aim is not to prevent all variation, but to manage it systematically.

These structured response steps should be documented as part of the workflow diagrams or guides already in place. A clear point of contact must be indicated for each type of operational incident, ensuring employees know where and how to escalate issues when necessary. Where staff report a recurring inefficiency, the process owner or designated lead should initiate a short, structured reflection with those involved. This could follow a format such as: (1) What was expected? (2) What occurred? (3) Why did it diverge? (4) What should be adapted?

This approach should also support traceability. Even if performance metrics are treated separately, the structured workflow must enable a backward look—linking inefficiency incidents to specific steps in execution. This strengthens the quality of feedback given to decision-makers or IT collaborators and prepares the process for future ML-based improvements.

Business Process Readiness – Automation Maturity

What is advised?

It is advised that logistics SMEs automate selected core processes that are repetitive, data-dependent, and operationally sensitive. Particular focus should be placed on automating shipment tracking, real-time inventory updates, and basic scheduling tasks. Automation at this stage does not require enterprise-grade systems; rather, accessible and scalable tools—ranging from built-in ERP functionalities to lightweight, cloud-based logistics platforms—can be sufficient to introduce reliability, speed, and data integrity to routine operations.

Why is it advised?

Automating essential logistics processes serves as a critical enabler of machine learning readiness. ML models require timely, structured, and consistently generated data to detect patterns and make predictions. Manual processes, even when well-documented, tend to introduce delays, errors, and inconsistencies that hinder model training and undermine confidence in outputs. For SMEs with limited staff and operational bandwidth, automation also frees up human resources for more value-added activities and enhances real-time responsiveness in dynamic logistics settings.

How to do it?

The first step involves selecting processes that (1) are already standardized, (2) occur frequently, and (3) depend on timely data. Shipment tracking, inventory reconciliation, and scheduling are often ideal starting points. SMEs should begin by mapping out how these processes are currently performed and where human input causes friction—such as delays in updating shipment status, stock counts being noted manually, or dispatching plans requiring back-and-forth calls.

Based on this, an automation opportunity should be defined. For shipment tracking, this might involve integrating a basic GPS-enabled tracking system with automatic status updates. For inventory, SMEs may opt for barcode scanning apps that sync with spreadsheets or warehouse software. For scheduling, automated calendar tools or rule-based dispatching add-ons can eliminate manual coordination. These solutions do not need to be comprehensive; narrow-scope, task-specific automation tools are often more manageable and budget-friendly.

If no in-house technical capacity exists, SMEs can rely on digitalization consultants, logistics software vendors, or applied research partners to recommend suitable tools. It is important, however, that operations staff are involved in tool selection to ensure alignment with existing workflows and to prevent resistance. Wherever possible, solutions should be piloted before full implementation. Pilots can run in parallel with manual systems over a short period to test performance, gain feedback, and refine integration.

Training must accompany any automation. A one-time demonstration followed by real-time support during the transition period is usually sufficient. Users should know what inputs are required, what outputs to expect, and how to escalate issues if they arise. Maintenance responsibility should be assigned clearly—even if this is a part-time or informal role—to ensure the solution remains reliable and relevant as processes evolve.

Business Process Readiness – Data-Driven Decisions

What is advised?

It is advised that logistics SMEs transition from intuition-based or anecdotal decision-making to a systematic use of structured logistics data, presented in clear, visual formats such as dashboards. These dashboards should be tailored to key decision-makers and updated in real time or at regular short intervals. The selected indicators must reflect the operational priorities of the SME—such as delivery performance, order cycle times, fuel usage, or vehicle utilization—and be aligned with the broader business context.

Why is it advised?

Data-driven decision-making creates the foundation for consistent, traceable, and performance-oriented business operations. In logistics, where timing, capacity, and coordination are constantly under pressure, access to up-to-date and actionable information enables SMEs to respond more quickly, allocate resources more effectively, and identify inefficiencies before they escalate. Furthermore, dashboards expose patterns that inform not only human decisions but also future machine learning applications, which rely on reliable feedback and visibility into historical performance. Without structured visibility, any ML initiative will lack interpretability and practical relevance.

How to do it?

The process begins with identifying a few core decisions that are regularly made and could benefit from better data support—for instance, rescheduling deliveries due to delays, adjusting warehouse staffing levels, or prioritizing customer service responses. For each decision type, the underlying information requirement must be clarified: What needs to be known to make this decision better? What data already exists? Where are the gaps?

With these questions answered, SMEs should implement lightweight dashboarding tools. These can range from Microsoft Excel dashboards refreshed with simple scripts, to free or low-cost platforms such as Google Data Studio, Power BI (free tier), or open-source solutions connected to cloud storage or CSV logs. Even visual whiteboard dashboards with printed charts can serve as a transitional step if digital tools are not yet in place.

Dashboards should be designed with end-users in mind: operational managers, dispatchers, or warehouse coordinators. This requires clear layouts, minimal clutter, and use of familiar terminology. Each dashboard should be built around a small number of focused indicators—preferably no more than five per view—so that insights can be absorbed at a glance. Typical indicators might include on-time delivery rates, number of open orders, or vehicle idle time.

It is critical that dashboards are integrated into routine decision-making. This may involve starting every shift with a five-minute review of the dashboard, using it to justify planning changes, or referring to it during weekly planning meetings. Where possible, one person should be responsible for maintaining dashboard accuracy and acting as the point of contact for interpreting updates or proposing changes.

Finally, SMEs should document a small number of cases where decisions were informed by dashboard insights and what outcomes resulted. This demonstrates internal value and lays a foundation for ML initiatives that aim to further automate such decision support in the future.

Business Process Readiness – Performance Monitoring

What is advised?

It is advised that logistics SMEs establish a small, targeted set of logistics performance indicators that are consistently tracked and used as the basis for routine reflection and operational refinement. These indicators—commonly referred to as KPIs—should be selected based on their relevance to the company's core logistics processes and should serve as signals for performance trends, disruptions, or opportunities for efficiency gains. Regular review cycles should be introduced to assess what the metrics indicate and whether corrective or improvement actions are warranted.

Why is it advised?

Defined KPIs transform abstract goals such as "faster delivery" or "fewer errors" into measurable, actionable targets. For SMEs, where resource constraints limit trial-and-error approaches, performance monitoring provides clarity on what works and where interventions are needed. More importantly, consistent KPI tracking creates the analytical backbone for future machine learning applications. ML models require historical records of quantified behavior to generate accurate predictions; without such performance data, ML initiatives are limited in scope, reliability, and business value.

How to do it?

The process begins by identifying which areas of the logistics operation are most critical or most prone to inefficiency. From there, no more than three to five KPIs should be defined initially. These may include indicators such as on-time delivery percentage, average warehouse throughput time, error rate in order picking, or vehicle utilization rate. The metrics must be simple to measure and interpret and should be built on data that is already being captured or can be gathered without significant disruption.

Measurement responsibilities must be assigned explicitly. In the absence of automated systems, basic tracking can be carried out manually using shared spreadsheets or forms, with periodic consolidation. For SMEs with basic ERP systems or transport management tools, dashboards or exports can be configured to generate reports at regular intervals—daily, weekly, or monthly, as advised in the previous **subsection Data-Driven Decisions**.

Equally important is the institutionalization of review routines. A specific moment should be allocated—for instance, the first 15 minutes of every Monday team meeting—to briefly examine the current KPI status. Deviations from expected values should trigger structured reflection, not blame. Teams should be encouraged to ask:

- Has something changed in how we operate?
- Can this be linked to a known bottleneck or external factor?
- Are our current routines still appropriate?

Findings from these reviews should be noted down, even briefly, and used to guide operational adjustments or testing of process improvements. This closes the feedback loop between monitoring and action, which is essential not only for short-term improvements but also for preparing the organisation to integrate ML insights into decision-making frameworks.

Strategic Alignment – ML Use Case Fit

What is advised?

It is advised that logistics SMEs identify a limited number of targeted machine learning use cases that are directly aligned with their operational realities and business goals, derived from the guidance on the **Process Standardization** and **Operational Inefficiencies subsections** of the **Business Process Readiness category**. These use cases should address bottlenecks or inefficiencies previously uncovered through structured workflow analysis and performance monitoring. The use cases must be narrow in scope, realistic given available resources, and capable of generating tangible value within the current logistics context.

Why is it advised?

The identification of relevant ML use cases is the linchpin between strategic intent and practical implementation. In many SMEs, ML is approached abstractly or reactively driven by external trends rather than internal need. This leads to mismatches between what the model can do and what the organisation requires. By anchoring use case selection in documented processes and previously diagnosed inefficiencies, SMEs ensure that ML efforts target areas with both sufficient data and operational relevance. This not only increases the likelihood of implementation success but also builds credibility and internal support for future scaling.

How to do it?

The process begins by revisiting operational areas where structured workflows have already been standardized and where recurring inefficiencies have been systematically addressed. These areas offer the cleanest and most consistent data environments, making them suitable candidates for ML experimentation. For example, if a company has standardized its dispatch process and consistently logs departure delays, a use case focused on *delay prediction* may be a strong fit.

Next, for each candidate area, SMEs should articulate the business question that ML could potentially address. These questions must be specific and actionable, such as: "Can we predict next week's inventory needs based on historical order volumes?" or "Can delivery routes be adjusted dynamically based on past congestion patterns?" These questions should then be reviewed in light of available data, the frequency of the underlying task, and the potential business impact of improving it.

To aid in this filtering, SMEs may construct a simple matrix with three evaluation criteria:

- Data Availability
- Operational Relevance
- Feasibility within Current Capabilities

Each potential use case is scored informally across these criteria to prioritize candidates. A use case such as route optimization might be rated highly if GPS and delivery logs are available and delays are costly, while automated pricing models may be excluded if no structured pricing history exists.

After narrowing down the options, one use case should be selected for low-risk piloting. At this stage, external collaborators—such as universities, applied research hubs, or software providers—can be consulted for technical guidance. It is critical, however, that the SME retains control over the use case framing, ensuring that the solution addresses their specific question and operates within the constraints of their environment.

Strategic Alignment – Competitive Benchmarking

What is advised?

It is advised that logistics SMEs conduct or commission a focused competitive analysis that examines how peer organizations or competitors are adopting machine learning technologies. This analysis should highlight specific practices, technologies, or service improvements enabled by ML and evaluate how these differ from the SME's own current capabilities. The aim is not to imitate, but to identify strategic opportunities or vulnerabilities in the firm's position and to inform prioritization of future ML initiatives.

Why is it advised?

Understanding how other firms in the logistics sector apply ML allows SMEs to benchmark their digital progress, identify areas where ML may offer competitive advantage, and avoid redundant or misaligned investments. Without such awareness, ML adoption risks being shaped internally in isolation, disconnected from evolving market expectations or customer standards. Competitive benchmarking introduces external strategic perspective into decision-making and strengthens the justification for use case selection, investment pacing, and partnership development. Furthermore, it can inspire more focused goal setting by showing what is feasible at a similar scale of operation.

How to do it?

For SMEs with limited capacity, the benchmarking process need not be elaborate or formal. It may begin with the review of publicly available sources—such as competitor websites, annual reports, service brochures, or case studies published by logistics platforms. Indicators of ML usage may include predictive delivery estimates, automated customer updates, dynamic pricing, or AI-enhanced routing. Informal sources such as sector-specific newsletters, webinars, or trade show presentations can also reveal early signals of digital adoption.

When direct analysis is impractical, SMEs may turn to applied research institutions, chambers of commerce, digitalization consortia, or sector innovation hubs. Many of these organizations offer reports, benchmarking services, or one-on-one support, often subsidized for SMEs. A company may request an ML readiness scan of its sector, or commission a short scan comparing technological trends in similarly sized logistics operators. These insights can then be tailored to the SME's own context, highlighting which gaps are worth addressing and which competitive positions can be reinforced.

Internally, results should be discussed with leadership and the operational team to interpret what the findings mean for the firm's positioning. The discussion should include questions such as: Are we falling behind in areas that customers value? Are there underserved service features that ML could help us offer? Are we wasting resources on manual tasks that others have already automated?

Where benchmarking uncovers a gap with strategic potential—such as lacking automated dispatch coordination where competitors already implement it—the SME may define a corresponding ML use case or begin planning a small pilot. If an opportunity is found—such as ML-supported fleet maintenance prediction being rare in the firm's delivery region—the SME may consider whether to become an early adopter and differentiate through service quality or cost efficiency.

Strategic Alignment – Financial Planning

What is advised?

It is advised that logistics SMEs establish a modest, clearly delineated budget for machine learning activities, even if limited in scale. This budget should cover the costs of piloting a specific ML use case, including data preparation, basic tooling or software, and—where relevant—external support. In parallel, rough ROI expectations should be formulated before deployment. These expectations may include cost reductions, time savings, or service-level improvements, depending on the focus of the ML use case.

Why is it advised?

Machine learning is not inherently cost-effective unless anchored in a purposeful business case. For SMEs with limited margins and tight operational cycles, any technology adoption requires careful financial justification. Without a predefined budget, ML efforts tend to stall midway, either due to resource depletion or shifting internal priorities. Likewise, without pre-defined ROI expectations, there is no consistent basis for evaluating impact, learning from results, or scaling successful pilots. Establishing both a budget and a financial objective ensures disciplined experimentation and enables SMEs to make informed decisions about continuation or expansion.

How to do it?

The budgeting process begins with selecting a single ML use case that has already been validated for operational relevance—such as route optimization, stock level forecasting, or delay prediction. For this use case, a short cost outline should be prepared. This outline should list required expenses, such as data cleaning or integration, external advice, prototyping tools (e.g., ML-as-a-service platforms), or light infrastructure (e.g., cloud storage or sensor hardware). For most SMEs, a range between €1,000 and €5,000 is realistic for a focused pilot involving limited variables.

To avoid burdening cash flow, the budget may be distributed over phases—starting with a feasibility phase that requires minimal investment. If feasible, SMEs may also explore grants, innovation vouchers, or university partnerships that provide technical labor at reduced cost. However, even when supported externally, the internal effort—staff time, communication, and alignment—should be costed to give a realistic total picture.

ROI estimation must be pragmatic. SMEs should avoid abstract metrics and instead translate expectations into concrete process outcomes. For example, if ML is applied to improve delivery scheduling, the expected benefit may be "reduction of idle driver time by 10%," which can then be translated into labor cost savings. If forecasting improves inventory control, the expected ROI might be "reduced stockouts by three per month," contributing to increased customer retention or fewer emergency orders.

These assumptions should be documented before implementation and revisited during and after the pilot. Even if the ROI is not immediately achieved, the SME will have a clearer view of what changed, how much it cost, and what could be improved. This financial transparency strengthens internal trust and prepares the ground for iterative investment in further ML applications.

Strategic Alignment – Sustainability Alignment

What is advised?

It is advised that logistics SMEs deliberately explore how machine learning can contribute to their environmental goals and identify at least one use case where this alignment is evident. This may include predictive tools that minimize resource consumption, reduce emissions, or prevent avoidable waste in logistics operations. When evaluating ML opportunities, environmental benefits should be considered alongside efficiency or cost-related outcomes, even if informally.

Why is it advised?

ML's value in logistics extends beyond cost reduction—it offers concrete opportunities to reduce the sector's environmental footprint. For SMEs under increasing pressure from clients, regulators, and funding bodies to demonstrate sustainability efforts, positioning ML as an ecological enabler strengthens both strategic relevance and reputational value. Additionally, framing use cases around sustainability tends to generate broader internal support and long-term justification for investment, especially when environmental performance is already a topic of discussion in supplier contracts, customer feedback, or reporting obligations.

How to do it?

The process begins by revisiting current logistics workflows or inefficiencies through a sustainability lens. Rather than asking "Where can ML save time or money?", SMEs should ask "Where are we currently consuming unnecessary fuel, generating excess waste, or using equipment inefficiently?" Examples might include vehicle idling, inefficient route planning, excessive packaging, or poorly timed maintenance that leads to asset loss.

Once a sustainability pain point is identified, the SME should consider whether there is enough data to support predictive modelling. For instance, if vehicle telemetry or delivery logs are available, these could be used to build an ML model predicting high-emission routes or optimal maintenance intervals. If inventory spoilage or energy use in warehousing is a concern, historical consumption data may provide a foundation for forecasting models or anomaly detection.

Environmental impact should then be added as an evaluation criterion when comparing ML use cases—alongside feasibility and ROI. Even where financial gains are modest, a sustainability-aligned ML use case may be prioritised if it strengthens compliance, branding, or partnership potential.

Where internal technical capacity is limited, SMEs may reach out to sector-specific innovation centres or universities with sustainability research agendas, many of which are actively looking for applied ML collaborations in transport, logistics, and supply chain. Pilot projects framed around ecological objectives are more likely to receive external support or co-funding than purely commercial applications.

Strategic Alignment – Customer Impact

What is advised?

It is advised that logistics SMEs assess how machine learning technologies can be used to enhance their customers' experience, particularly in areas where speed, communication, and service reliability are crucial. This analysis should identify which pain points in the customer journey are most frequently reported or operationally challenging, and whether ML-driven solutions—such as predictive updates, smart notifications, or conversational support—can offer improvements without overcomplicating service delivery.

Why is it advised?

While many ML use cases in logistics aim to optimize internal operations, the customer-facing benefits are often the most visible and impactful. In competitive logistics environments, clients increasingly expect fast, reliable, and transparent services. ML applications that anticipate delays, personalize communication, or streamline responses can directly strengthen customer satisfaction and loyalty. Moreover, demonstrating improvements in service quality creates internal support for ML adoption and positions the SME more competitively in the market. Understanding the customer-facing impact of ML ensures that technological investment aligns not only with internal efficiency, but also with external value creation.

How to do it?

The analysis should begin with a mapping of key customer interactions across the logistics workflow—such as booking confirmation, delivery status updates, issue reporting, or proof of delivery. For each interaction point, the SME should identify common service problems or delays (e.g., clients requesting updates by phone, uncertain delivery windows, or lack of visibility during order fulfillment). This mapping can be informed by direct staff feedback, customer complaints, or informal discussions with long-term clients.

Based on this map, the SME can explore targeted ML use cases known to enhance customer experience. These might include predictive delivery notifications based on historical route delays, AI-powered chat assistants to handle repetitive tracking inquiries, or dynamic ETA adjustments sent automatically to customers. If needed, examples from similar SMEs can be drawn from logistics industry case studies, supplier presentations, or sector webinars.

The next step involves selecting one or two feasible ideas and evaluating their practical fit. This includes considering available data (e.g., delivery timestamps, delay reasons, tracking logs), potential integration with current customer communication channels (e.g., SMS, email, internal portals), and the ability to pilot without full system overhaul.

The analysis should be documented in short form: what issue is being addressed, what the proposed ML intervention is, what data it relies on, and how it will affect the customer experience. This document should be reviewed jointly by operations and customer-facing staff to ensure the solution is both technically grounded and aligned with actual client expectations.

Finally, if a pilot is conducted, the SME should include a feedback mechanism—either through staff observation, client follow-ups, or service-level indicators—to validate whether the intervention improved satisfaction or created unintended effects.

Security & Regulatory Compliance – Data Protection & Privacy

What is advised?

It is advised that logistics SMEs implement basic data protection measures that include formal policies, encryption of stored data, and internal rules restricting employee access to sensitive information. These measures should be aligned with legal obligations such as GDPR and proportionate to the size and complexity of the SME's operations. While full compliance frameworks may be excessive at this stage, clear principles and simple technical safeguards must be in place to ensure that personal and commercially sensitive logistics data is handled responsibly.

Why is it advised?

Logistics SMEs increasingly manage data with both operational and personal dimensions—ranging from shipment details and vehicle locations to customer addresses and driver identifiers. If this data is left unprotected or widely accessible internally, the firm risks breaches that can damage its reputation, breach legal requirements, and expose it to client or employee complaints. Furthermore, as machine learning systems rely on structured data inputs, safeguarding that data becomes integral to both system integrity and ethical compliance. Establishing protection and privacy protocols early also ensures the SME is well-prepared for future data partnerships or client audits.

How to do it?

The first step is to draft a short internal data protection policy. This document should state what kinds of data are collected (e.g., customer delivery addresses, route logs, incident reports), why the data is needed, how it is stored, and who has access. The policy should also clarify what counts as sensitive data and define handling practices accordingly. SMEs can use publicly available templates adapted for small enterprises to reduce the drafting burden.

Next, stored data—whether in spreadsheets, databases, or software systems—must be encrypted. For cloud-based tools, SMEs should ensure that encryption is enabled at rest and in transit, which is standard in most reputable platforms. For locally stored files, password protection and basic encryption tools (e.g., encrypted ZIP folders or software with encryption features such as VeraCrypt) can be used. If proprietary logistics software is employed, settings should be reviewed to ensure that encryption is active.

Role-based access should be enforced through simple user privilege schemes. For example, warehouse staff may require access to order numbers and dispatch times, but not to customer names or payment details. SMEs using shared drives or software should create permission groups—logistics, finance, admin—so that users only access the data needed for their tasks. In small teams where such restrictions may seem unnecessary, role-based limitations still serve to reduce accidental data misuse and establish clear boundaries for future scalability.

All of the above should be supported by a short onboarding module for new employees, in which basic data handling expectations are explained. In practice, this can be achieved with a single-page checklist signed during hiring or a five-minute walkthrough during orientation.

Security & Regulatory Compliance – Cybersecurity Measures

What is advised?

It is advised that logistics SMEs establish and maintain basic but structured cybersecurity measures that protect their digital infrastructure from external threats and internal vulnerabilities. These measures should include a written cybersecurity policy, active firewall protection, regular updates to all connected devices and software, and periodic vulnerability checks. For ML readiness, particular attention should be given to securing data flows between digital systems and ensuring that connectivity within the SME's network does not introduce unmonitored risk.

Why is it advised?

As logistics SMEs become increasingly reliant on digital systems for operations, planning, and ML experimentation, they also become more exposed to cyber threats—such as ransomware, phishing, and system compromise. These attacks can paralyze service delivery, erase operational data, and result in client contract breaches. Even small vulnerabilities—such as an outdated operating system or a weakly secured Wi-Fi network—can serve as entry points for attackers. Moreover, ML systems often operate across multiple data sources and applications, creating integration points that must be shielded. A failure to invest in basic cybersecurity protections can thus undermine both short-term continuity and long-term digital growth.

How to do it?

Cybersecurity should begin with the creation of a short, plain-language cybersecurity policy. This document should list key protection areas—device security, software update routines, password hygiene, firewall use, and safe internet practices. It should assign responsibility for implementation—typically to a manager with basic IT competence or an external support provider—and define response procedures in case of breaches. Templates suitable for SMEs are widely available through cybersecurity centers or public sector initiatives focused on small business resilience.

Firewalls must be activated on all workstations, routers, and external access points. Most modern operating systems and routers include built-in firewall capabilities that can be enabled through configuration settings. For SMEs using remote work or off-site mobile devices (e.g., drivers accessing schedules via smartphone), secure connections via VPNs or encrypted mobile apps should be established.

Regular updates are essential. All software—including operating systems, anti-virus tools, logistics platforms, and plug-ins—must be kept current. Where automatic updates are available, these should be enabled. Where manual updates are required, one employee should be assigned a recurring calendar reminder to check and apply them.

Basic vulnerability assessments can be carried out quarterly. These need not be extensive penetration tests but may consist of using free scanning tools (e.g., Microsoft Defender, Avast Business Hub) to review device security and identify unpatched systems or unsecured ports. SMEs may also request simplified audits or awareness workshops from public IT security centres, industry groups, or educational institutions with cybersecurity programmes.

Security & Regulatory Compliance – Regulatory Compliance

What is advised?

It is advised that logistics SMEs conduct a proactive review of the regulatory environment surrounding the data and operational processes involved in their machine learning initiatives. This includes identifying relevant legal obligations—such as data protection, employment transparency, and sector-specific regulations—as well as adopting basic ethical safeguards. The goal is to ensure that ML deployment does not unintentionally violate customer rights, expose the SME to liability, or undermine employee trust.

Why is it advised?

Although ML projects in SMEs are often small in scale, they can still trigger significant legal and ethical concerns if deployed without appropriate oversight. For example, if an ML system uses driver performance data without consent, or if automated decisions affect client treatment unequally, the SME may face reputational or legal consequences. Furthermore, compliance not only protects against risk but strengthens the credibility of the ML initiative internally and externally, enabling smoother integration, especially in client-facing contexts. Establishing legal and ethical alignment early also facilitates scaling later, when audits or partnerships may require demonstrable due diligence.

How to do it?

The compliance process should begin by identifying what data will be used in the ML initiative, how it will be collected, who will have access to it, and what decisions the system will influence. This mapping exercise should be documented in a brief internal summary, which becomes the basis for further assessment.

SMEs should then consult publicly available resources or contact local regulatory or advisory bodies to determine which frameworks apply. In the European context, this will almost always include GDPR, especially if personal data (e.g., driver ID, customer addresses) is processed. If data is collected via tracking systems, sensors, or third-party platforms, contractual obligations and privacy disclosures must be checked. In some cases, the SME may also need to assess fairness—e.g., whether the ML model could unintentionally favour certain clients, drivers, or regions based on biased data patterns.

If legal expertise is not available internally, SMEs may request support from regional digitalization agencies or sector federations. These bodies often offer free or subsidized scans or compliance workshops for SMEs. In more sensitive use cases—such as predictive models influencing personnel allocation or contractual prioritization—legal consultation is strongly advised, even if only for a short review.

Ethical alignment should also be considered. This involves establishing internal principles for ML use, such as "employees must be informed when automated tools evaluate their performance" or "decisions proposed by ML will always be reviewed by a human before execution." These principles do not need to be formalized into policies but should be clearly communicated and consistently applied.

Finally, all ML-related documentation should include a short section on compliance—what rules apply, what measures were taken, and who is responsible. This enhances transparency and provides a traceable record in the event of audits or future scale-up.

Security & Regulatory Compliance – Risk Management & Security Governance

What is advised?

It is advised that logistics SMEs establish basic but formalized processes for identifying, assessing, and responding to digital risks that may affect their systems, data, and service continuity. These processes should include recurring risk reviews, periodic security audits (even if light-touch), and documented contingency plans to respond to events such as cyberattacks, unauthorized access, or data loss. Governance should include clear accountability and reporting lines for security-related decisions.

Why is it advised?

As SMEs increasingly integrate digital systems—including machine learning tools—into their operations, they face heightened exposure to security incidents. Unlike isolated technical measures (e.g., firewalls or passwords), risk management ensures that threats are anticipated, prioritized, and addressed systematically. In logistics, where digital disruptions can halt deliveries or expose sensitive route data, unpreparedness leads to significant operational and reputational harm. Establishing governance mechanisms allows SMEs to not only respond faster during incidents, but also to make informed decisions about risk trade-offs during ML adoption and system scaling.

How to do it?

The process begins by assigning one person—typically someone with managerial or technical responsibility—to coordinate security oversight. This person leads a basic risk identification exercise, listing digital assets (e.g., shipment data, customer records, ML models), potential threats (e.g., malware, data leaks, downtime), and vulnerabilities (e.g., weak access protocols, outdated software). A simple spreadsheet or checklist can be used to capture this.

Next, SMEs should schedule light internal security audits, ideally once or twice per year. These audits may involve checking for unused accounts, testing backup recovery, verifying that access controls still reflect staff roles, or simulating a data loss event. SMEs with limited technical resources can follow publicly available SME-focused security audit templates or request support from regional cybersecurity advisory bodies.

A contingency or incident response plan must also be drafted. It should clearly outline:

- What constitutes a security incident?
- Who must be informed and in what order?
- How operations will be maintained or paused?
- Where recovery tools or backups are stored?
- How stakeholders (e.g., clients, partners) will be notified?

This plan should be brief, printed or stored accessibly, and known to staff with relevant duties. It should be reviewed annually or whenever systems change.

Governance also requires clarity in decision-making. Security-related decisions—such as approving cloud providers, exposing ML models externally, or integrating third-party tools—should follow a short internal review protocol, ideally involving more than one person. This distributes accountability and ensures that risks are weighed against benefits before implementation.

Security & Regulatory Compliance – Access Control & Authentication

What is advised?

It is advised that logistics SMEs adopt role-based access control (RBAC) mechanisms to ensure that employees only access the data and systems required for their functions. Additionally, multi-factor authentication (MFA) should be enabled for all systems that handle sensitive data or critical operational functions, such as ML models, route planning tools, or cloud storage. These measures serve to contain the impact of internal errors or external breaches and preserve the integrity of the SME’s digital environment.

Why is it advised?

In SMEs with lean structures and overlapping responsibilities, informal access practices often go unchecked. Staff may retain system access after role changes, or sensitive data may be openly accessible across shared drives. As machine learning and data-centric tools are introduced, these access inconsistencies become high-risk points. RBAC and MFA reduce the likelihood of unauthorized access—whether due to phishing, human error, or malicious intent. Together, they establish basic security hygiene without requiring complex infrastructure and provide necessary controls over ML-related data assets and outputs.

How to do it?

Implementation begins by mapping out the SME's digital systems—e.g., logistics platforms, analytics dashboards, cloud repositories—and identifying who currently has access to each. This can be done with a simple table listing systems, users, access rights, and the justification for each permission. Redundant or excessive permissions should be removed immediately.

Next, define a small number of access roles based on actual job responsibilities. For example: *Warehouse Staff*, *Drivers*, *Operations Coordinators*, *Finance*, *IT Support*.

Each role should have a defined access profile, specifying what files, dashboards, or tools are required and what should be restricted. These profiles should then be implemented within the system settings—whether through built-in user management in SaaS platforms or via file-sharing settings in Google Drive or Microsoft 365.

For authentication, MFA should be activated for all accounts with access to sensitive or administrative systems. This typically involves requiring users to verify their identity through a second factor—such as a mobile code or authentication app—in addition to their password. Most modern systems offer MFA as a built-in option, and many offer free tiers that support it. The SME should prioritise enabling MFA for email accounts, cloud dashboards, remote login tools, and anything linked to customer or delivery data.

Once implemented, access rules and MFA policies should be documented briefly and shared with staff. Onboarding checklists must include access setup aligned to roles, and offboarding should include immediate access removal. A designated staff member should review access logs and permissions quarterly, updating them if organisational roles shift or tools are added.

External Dependencies & Ecosystem Readiness – Vendor IT Maturity

What is advised?

It is advised that logistics SMEs evaluate the digital maturity of their IT vendors and maintain an active dialogue to ensure that external tools and platforms can integrate with their internal processes and data infrastructure. This includes understanding vendor data formats, update protocols, and system architecture before adopting new tools—especially when the tools feed into or depend on machine learning workflows. Compatibility assessments should precede onboarding and continue throughout the collaboration.

Why is it advised?

For SMEs exploring ML, external tools—such as fleet tracking systems, warehouse platforms, or analytics dashboards—often serve as key data sources or integration points. If these systems are outdated, closed, or technically incompatible, they obstruct data flow and limit ML feasibility. Conversely, collaboration with digitally mature vendors facilitates structured data exchange, reduces manual intervention, and supports smoother experimentation. Ensuring IT compatibility also helps SMEs avoid vendor lock-in, reduce costly workarounds, and retain control over their digital ecosystem.

How to do it?

SMEs should begin by identifying the vendors that provide core operational systems (e.g., transport management systems, order handling platforms, IoT hardware). For each, a short evaluation should be made, covering:

- Whether the vendor provides data export or API access
- The format and structure of the data provided (e.g., CSV, JSON, XML)
- The frequency and reliability of data updates
- Whether the system allows integration with third-party analytics or ML tools

A basic vendor IT maturity checklist can be created and updated annually. SMEs should use this checklist when considering new vendor tools, especially those handling logistics data that could be relevant to forecasting, optimization, or predictive maintenance.

Where maturity gaps are identified—such as closed data environments or outdated interfaces—the SME should raise concerns during routine vendor contact. This can be done informally (e.g., via support tickets or sales reviews) or formally (e.g., through SLAs or procurement criteria). Vendors should be asked whether APIs are available, whether documentation can be provided, and whether there is experience in supporting ML-related access or use cases.

Where vendors show resistance or limitations, SMEs should document the issue and evaluate alternatives. If switching is not feasible, they may consider building simple adapters or working with consultants to extract and standardize relevant data for ML experimentation. For highly critical systems, future vendor selection should explicitly include IT maturity and ML compatibility as key decision criteria.

External Dependencies & Ecosystem Readiness – Industry Trends

What is advised?

It is advised that logistics SMEs monitor machine learning developments in the logistics and transport sector to understand how innovation is evolving and what expectations may emerge across the value chain. They should regularly benchmark their position relative to peers and identify trends that could signal emerging risks or opportunities. The aim is not to imitate industry leaders, but to maintain enough foresight to align ML initiatives with sector direction, client expectations, and technology availability.

Why is it advised?

Machine learning evolves rapidly, and SMEs that lack visibility into broader industry dynamics risk investing in outdated solutions or missing critical windows of adoption. For logistics-focused SMEs, staying attuned to ML trends allows for timely positioning—whether that means exploring predictive maintenance before it becomes standard, or being ready to offer smart delivery options as customers begin expecting them. Trend awareness also strengthens internal strategic alignment by providing reference points when evaluating potential ML use cases or allocating resources.

How to do it?

The SME should designate a simple structure for periodic trend monitoring. This can be informal but consistent—such as quarterly internal reviews of sector publications, ML-focused logistics webinars, trade association briefings, or innovation newsletters. A spreadsheet or shared document can be used to capture relevant trends, tagging them by area (e.g., last-mile logistics, fleet optimization, sustainability, automation) and noting which firms are adopting what approaches.

Benchmarking does not require detailed competitive analysis. Instead, SMEs should identify a few reference points—such as regional competitors, partners, or digital leaders in logistics—and assess what ML-related features or tools they have adopted. These can be drawn from public sources: service descriptions, product launches, news articles, or conference presentations. Key observations should be discussed internally during planning or technology review sessions.

Participation in sector events, whether in person or online, can further enrich understanding. SMEs should target forums that bridge logistics and digital innovation, where use cases are shared by practitioners. Public funding calls or innovation programmes can also serve as indicators of what technologies are gaining traction or support.

Finally, when evaluating their own ML progress, SMEs should reflect not only on how advanced they are but also on whether their efforts are relevant to where the sector is heading. This alignment ensures that pilot projects and investments maintain long-term value and avoid becoming siloed or obsolete.

External Dependencies & Ecosystem Readiness – External Data

What is advised?

It is advised that logistics SMEs identify and incorporate relevant external data sources into their operational and decision-making environments, particularly where such data can improve the accuracy, responsiveness, or adaptability of machine learning applications. These sources may include real-time traffic feeds, weather updates, fuel price indexes, economic forecasts, or public logistics datasets. Integration should serve a specific function, such as improving demand prediction, enhancing route efficiency, or contextualizing shipment risks.

Why is it advised?

Machine learning models depend not only on internal process data but also on external context to achieve robustness and accuracy. In logistics, real-world variables—such as traffic delays, seasonal fluctuations, or economic slowdowns—directly affect delivery performance, cost structures, and inventory cycles. SMEs that rely solely on internal historical data limit their model's adaptability and overlook the broader conditions that influence outcomes. Integrating external data sources strengthens decision support, reduces blind spots, and prepares the SME for more dynamic, context-aware ML solutions.

How to do it?

The first step is to identify which external factors regularly affect the SME's logistics operations. For instance, urban traffic may influence delivery times, fuel price volatility may impact route planning costs, or holidays may shift demand cycles. For each factor, SMEs should determine whether relevant external data is publicly or commercially available. Many sources are free or low-cost—such as Google Maps APIs for traffic data, public meteorological feeds, or open government datasets on freight trends.

Once suitable sources are identified, SMEs should explore simple integration paths. For example, traffic data can be pulled into routing tools via API, weather data can be referenced in scheduling spreadsheets, and macroeconomic indicators can be used to adjust demand forecasts during planning cycles. These integrations can be lightweight—starting with periodic manual imports or small scripting solutions—and do not require full automation from the outset.

For SMEs already working with external IT vendors or software platforms, it is recommended to check whether the tools already support third-party data inputs. Many modern logistics systems allow for real-time data feeds, webhook integrations, or API extensions. SMEs should use this opportunity to expand the relevance and responsiveness of their systems.

Finally, when building or evaluating an ML use case, external data should be considered as a potential input variable. A short internal workshop may be held to brainstorm: *"What outside signals affect this prediction, and how can they be captured?"* This prompts both technical and business teams to recognize the role of context and increases the strategic value of ML pilots.

External Dependencies & Ecosystem Readiness – AI Talent

What is advised?

It is advised that logistics SMEs ensure they have access to basic AI/ML expertise by establishing formal relationships with individuals or external partners who can support the design, development, and interpretation of machine learning applications. This expertise need not be internalized through full-time hiring; it may be secured through part-time consultants, freelance professionals, university partnerships, or specialized service providers. The key requirement is to ensure that technical knowledge is available when ML exploration or implementation begins.

Why is it advised?

While SMEs typically lack the resources to build full in-house data science teams, a complete absence of AI expertise creates dependency on black-box tools or uncritical vendor offerings. Without at least basic expert input, SMEs risk misinterpreting ML outputs, underestimating system requirements, or implementing inappropriate models. Access to trusted AI talent enables better alignment between technical possibilities and business realities, increases the likelihood of successful pilot outcomes, and ensures that decisions are informed by domain-appropriate understanding.

How to do it?

The SME should first clarify what kind of AI expertise is required. In most early-stage cases, this involves support with use case scoping, data readiness review, model selection, and performance interpretation. These needs can be addressed without hiring a full-time data scientist. SMEs may begin by contacting regional AI support organizations, public digitalization initiatives, or university innovation offices, many of which maintain networks of AI professionals available for SME collaboration.

Alternatively, the SME can explore low-commitment advisory arrangements—such as engaging a consultant for a fixed number of hours during a pilot phase or subscribing to an IT-as-a-service platform offering ML capabilities bundled with technical support. These models offer flexibility and cost control, allowing the SME to scale engagement based on actual ML adoption needs.

When working with external AI talent, the SME should ensure that the expert is not only technically competent but also capable of translating business needs into technical requirements and vice versa. In small organizations, communication and mutual understanding between logistics staff and technical experts are often more important than advanced modelling knowledge.

To prepare for collaboration, the SME should create a short internal briefing document summarizing what business process is targeted, what data is available, and what problem the SME is trying to solve. This ensures that the expert's time is used efficiently and that expectations are grounded in the organization's actual context.

External Dependencies & Ecosystem Readiness – Research Partnerships

What is advised?

It is advised that logistics SMEs proactively seek out and establish partnerships with research institutions, AI-focused academic departments, or sector-specific innovation groups. These partnerships should be purpose-driven, aligned with the SME's operational needs, and structured around concrete ML-related goals—such as prototyping use cases, validating data strategies, or experimenting with new algorithms in a low-risk setting.

Why is it advised?

SMEs often lack the internal capacity and resources to explore emerging technologies in depth. Research partnerships provide a structured and cost-effective way to experiment with ML while drawing on cutting-edge expertise, access to advanced tooling, and tested methodologies. For logistics-focused SMEs, such collaborations can lead to customized solutions based on real-world data, early access to talent, and visibility in innovation ecosystems. Moreover, research institutions often offer publicly funded programmes or student-led projects, allowing SMEs to test ML ideas with minimal financial risk. This builds not only technical capability but also strategic confidence in adopting more complex systems over time.

How to do it?

The SME should first identify institutions or research groups with a known interest in logistics, supply chain optimization, applied AI, or industrial analytics. This can be done through local innovation hubs, university websites, regional chambers of commerce, or digitalization support networks. SMEs should prepare a short concept note outlining their challenge, what data is available, and what kind of support or experimentation they are seeking. Even if the SME has no prior research experience, many applied universities have matchmaking offices specifically for SME collaboration.

Engagement can begin with informal discussions, invitations to thesis collaboration, or participation in co-creation programmes. Many partnerships are structured around student projects, subsidized pilots, or knowledge vouchers, with clear roles and deliverables. The SME should clarify what outcomes they expect—such as a working prototype, performance evaluation, or workflow integration suggestions—and what constraints (time, data, technical access) must be considered.

It is also important to maintain regular contact throughout the partnership, assigning an internal coordinator who understands both the operational context and the collaboration goals. This person ensures alignment, provides timely feedback, and helps transfer knowledge internally once the collaboration concludes.

Scalability & Long-Term Viability – IT Scalability

What is advised?

It is advised that logistics SMEs adopt cloud-based or hybrid IT infrastructure capable of scaling up in response to increasing computational and data-processing demands driven by machine learning workloads. This includes establishing an environment where storage, compute power, and bandwidth can grow without causing downtime or requiring full system replacement. The aim is to ensure that infrastructure is not a bottleneck as ML becomes embedded in more processes and decisions.

Why is it advised?

Unlike conventional software, ML solutions often involve larger datasets, iterative retraining cycles, and processing-heavy tasks—such as forecasting, anomaly detection, or optimization. As SMEs expand their use of ML across domains, static or underpowered infrastructure can lead to delays, crashes, or data loss. Cloud or hybrid environments offer elasticity: the ability to allocate resources when needed and release them when not, which is crucial for both pilot testing and production scaling. Moreover, cloud solutions reduce the need for upfront investment in hardware and allow SMEs to experiment without long-term commitments. Scalability enables continuity, speed, and resilience—particularly in logistics contexts where timing and coordination are critical.

How to do it?

The SME should begin by assessing whether its current infrastructure can handle data growth and heavier ML-related workloads. Key questions include: How quickly can storage be expanded? Can new software be deployed without downtime? Are servers, if used locally, operating near capacity? If limitations are found, the SME should explore transitioning to a cloud-first or hybrid model that supplements existing tools with cloud capabilities.

For early-stage scalability, SMEs can adopt modular cloud services with pay-as-you-go models, such as cloud file storage, cloud-based ML platforms (e.g., Google Vertex AI, Azure ML), or serverless functions for occasional compute tasks. These services allow SMEs to run models, store outputs, and scale selectively without maintaining in-house servers.

Hybrid strategies are also suitable, particularly for SMEs that wish to keep core operations on local systems while offloading compute-intensive ML processes to the cloud. This may involve syncing local datasets with a cloud environment or using cloud APIs to run ML models externally and return results into existing systems.

Infrastructure planning should include bandwidth and redundancy considerations, especially for SMEs operating across multiple warehouses, depots, or delivery hubs. Cloud-based backups and remote-access configurations should be introduced to protect operations in the event of hardware failure or peak load surges.

As use grows, the SME should monitor its resource utilization using built-in dashboards from cloud providers or third-party optimization tools. This enables ongoing alignment between ML usage and infrastructure capacity, ensuring performance remains stable as adoption scales.

Scalability & Long-Term Viability – Infrastructure Flexibility

What is advised?

It is advised that logistics SMEs develop their IT infrastructure in a way that allows targeted integrations with ML tools, without requiring a complete overhaul of existing systems. This involves enabling modular expansions—such as add-ons, connectors, or interface layers—that permit machine learning tools to interact with logistics operations (e.g., warehouse management, route scheduling, or inventory systems). The goal is not full integration, but structured flexibility: allowing ML to extend functionality through deliberate connection points.

Why is it advised?

For logistics SMEs, most IT systems have evolved incrementally, leading to heterogeneous environments with limited internal cohesion. A full digital transformation is often infeasible. However, by enabling partial and structured integrations, SMEs can selectively introduce ML capabilities—such as anomaly detection or demand prediction—where they add the most value. This approach reduces cost, preserves stability, and minimizes disruption while still enabling innovation. It also lays the groundwork for long-term interoperability, ensuring that future digital components can be layered in without requiring system replacement.

How to do it?

The SME should begin by reviewing its core operational software: order management, fleet tracking, warehouse control, etc. For each system, a basic technical mapping should be done to determine whether data can be exported (e.g., CSV, XML), APIs are available, or third-party tools are supported. Even if integration is limited, the presence of structured data access points is often sufficient to support lightweight ML pilots.

Next, the SME should prioritize areas where ML outputs can provide immediate value without needing full system integration. For example, if delivery schedules are managed via spreadsheet or semi-digital tools, a simple ML model for delay prediction can export results into the same format, allowing planners to act without changing their workflow. Similarly, inventory forecasting can be enhanced through a parallel ML dashboard that reads from and writes to existing data exports.

When possible, the SME should introduce middleware tools or custom scripts to bridge systems—translating data between legacy tools and ML components. Low-code platforms or integration services (e.g., Zapier, Make) may support such connections without deep technical work. These bridges should be documented, tested for reliability, and monitored to ensure consistent data flows.

Finally, new IT investments should be evaluated with flexibility in mind. Systems that support APIs, modular extensions, or third-party integrations should be favoured over rigid, proprietary tools. This allows the SME to gradually build an infrastructure that can adapt over time, supporting not only ML, but broader digital maturity.

Scalability & Long-Term Viability – Cost Optimization

What is advised?

It is advised that logistics SMEs actively monitor, evaluate, and optimize the costs associated with machine learning initiatives—not only during initial implementation but throughout the full lifecycle. This includes assessing direct expenses (e.g., software subscriptions, infrastructure use, consultancy hours) as well as indirect costs (e.g., staff time, data preparation efforts, retraining frequency). A scalable cost strategy should be put in place, allowing the SME to adjust investment levels based on usage, business growth, or changing priorities.

Why is it advised?

ML implementation does not end with deployment. As systems scale, the associated costs can grow unpredictably—particularly if external tools charge per usage, models require frequent retraining, or infrastructure scales inefficiently. For SMEs operating on narrow margins, unanticipated expenses can quickly erode value or lead to the abandonment of useful tools. A cost optimization strategy ensures that ML remains financially sustainable and proportionate to the SME's size and maturity. It also enables gradual growth, allowing the SME to align technical scaling with operational and financial capacity.

How to do it?

The SME should begin by mapping the current and expected cost components of each ML use case. This includes software licenses, cloud processing costs, API access fees, consulting hours, and staff time allocated to managing models or preparing data. These should be documented in a simple cost breakdown and reviewed at regular intervals—ideally aligned with quarterly planning cycles.

Next, usage-based services should be evaluated for cost efficiency. If the SME is using cloud computing resources, for instance, usage patterns can be monitored to identify unnecessary processing or idle time. SMEs should take advantage of pricing calculators or usage dashboards offered by most service providers to explore optimization opportunities. Where possible, less frequent retraining schedules, batch processing, or simpler models may offer substantial savings without compromising performance.

Furthermore, SMEs should adopt a "right-sized" approach when scaling ML. Instead of expanding all at once, they should identify which processes or teams benefit most from ML and scale incrementally prioritizing the highest impact areas. This staged approach enables cost control while learning from implementation experience.

To support long-term optimization, SMEs can also explore public funding schemes, innovation subsidies, or joint ventures that defray the cost of technical expansion. Universities or public AI hubs may offer low-cost infrastructure or talent, which can reduce internal investment without limiting development.

Scalability & Long-Term Viability – Model Maintenance

What is advised?

It is advised that logistics SMEs implement a lightweight but systematic approach to maintaining machine learning models. This includes mechanisms for tracking model performance, deciding when retraining is needed, and managing model versions to prevent confusion or unintended regressions. The approach should be adapted to the SME's scale—practical, transparent, and integrated into day-to-day operations—without requiring complex infrastructure.

Why is it advised?

Unlike static software, ML models degrade over time. This phenomenon—known as model drift—occurs when the data the model sees in production differs from the data it was trained on. For logistics SMEs, whose environments are shaped by fluctuating demand, traffic patterns, seasonal conditions, and policy changes, such shifts are frequent. Without regular monitoring, a model's outputs may become misleading, undermining trust and leading to poor decisions. Moreover, without version control, it becomes unclear which model was used when, making outcome tracing and iterative improvement difficult. Structured maintenance ensures that models remain useful, accountable, and aligned with reality as operations evolve.

How to do it?

The SME should begin by defining key performance indicators (KPIs) for each ML model in use. These should be meaningful to the specific application—such as prediction accuracy for delay forecasts, percentage of correct alerts for inventory risks, or actual-versus-expected delivery times. These indicators must be tracked regularly (e.g., monthly or after every 500 predictions), using either automated logging or simple manual sampling.

Next, thresholds should be established for triggering retraining. These may include performance degradation beyond a defined margin, the appearance of new data patterns, or the introduction of new product lines, routes, or policies that the original model was not trained on. Retraining routines should be documented: what data will be used, how the model will be evaluated, and who is responsible for the process.

For version control, each model update should be clearly labelled and stored with basic metadata: version name, training dataset period, features used, performance metrics, and deployment date. This can be managed using a structured folder naming convention and a shared log file—no complex infrastructure is required. If external parties assist with model development, they must be contractually required to hand over versioned and reproducible outputs.

Finally, SMEs should test updated models in a controlled setting before replacing existing versions. This may involve comparing predictions side-by-side over a short period or deploying the new version to a limited user group. This ensures continuity and allows staff to regain confidence before full integration.

Scalability & Long-Term Viability – Governance

What is advised?

It is advised that logistics SMEs establish a structured governance framework that defines how decisions about machine learning systems are made, monitored, and adjusted over time. This framework should allocate roles, specify accountability for ML outcomes, and ensure that model use remains aligned with business goals, ethical principles, and operational requirements. The aim is to support the long-term viability of ML use—not just its technical deployment—by embedding oversight into strategic and operational structures.

Why is it advised?

Unlike one-off IT tools, ML systems are dynamic, data-dependent, and probabilistic. They require ongoing supervision to remain useful, fair, and safe. Without a governance structure, SMEs risk adopting models that drift from business objectives, become outdated without notice, or produce outputs that are misused or misunderstood. Establishing a governance framework ensures clarity over who owns what, when models should be retrained or retired, how results are interpreted, and how feedback is incorporated. It also builds internal trust and accountability, which are essential for scaling ML use beyond isolated pilots.

For logistics-focused SMEs, where operational decisions often carry immediate and material consequences (e.g., dispatching, fleet routing, load balancing), governance helps safeguard that ML systems support—not substitute—human decision-making. It ensures that performance, compliance, and organisational learning are systematically managed.

How to do it?

The SME should begin by defining a governance structure tailored to its size and complexity. This need not be elaborate. It can be as simple as assigning roles across three domains:

- Ownership – Who is responsible for approving ML use cases and ensuring alignment with business objectives?
- Oversight – Who monitors model performance and flags deviations or ethical concerns?
- Operations – Who manages day-to-day usage, inputs, and outputs of ML systems?

A short document should be drafted to codify these roles, along with decision-making criteria—such as when to escalate issues, how to determine model usefulness, or what thresholds require retraining. If external data or third-party platforms are involved, governance should also include guidelines for vendor accountability and data usage boundaries.

Next, the SME should create simple review mechanisms. This may involve quarterly check-ins where the ML system's performance, impact, and relevance are assessed against expectations. Feedback from users (e.g., planners, dispatchers, warehouse staff) should be formally collected and considered, especially when ML outputs are used to support time-sensitive decisions.

Lastly, responsible AI principles should be explicitly included—even in basic form. These might state that: ML outputs will not be used for automated personnel evaluation, or that predictive decisions will always be reviewed by a human before implementation. Including such principles signals the SME's commitment to ethical and transparent usage, especially as it scales ML across more processes.

J) Case Studies

J1) Demand Forecasting

A

A- Introduction of problem and process (current BPMN)
- Readiness Score (Radio chart visualization)
- Guidance based on assessment score
- Desired State

J2) Route Optimization

A

A A- Introduction of problem and process
- Readiness Score (Radio chart visualization)
- Simulated Guidance based on assessment score

J3) Spare Parts Management

A

Introduction of problem and process.
- Readiness Score (Radio chart visualization).
- Simulated Guidance based on assessment score.