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

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Abstract

Logistics small and medium-sized enterprises (SMEs) represent a critical component of the European supply chain ecosystem, yet they face persistent challenges in adopting machine learning (ML) technologies due to limited resources, sector-specific constraints, and a lack of clear implementation guidance. Existing ML readiness frameworks often overlook the unique operational realities of logistics SMEs and fail to provide actionable, context-sensitive support. This study introduces a modular, sector-specific framework to assess and improve ML readiness in logistics SMEs by combining diagnostic evaluation with structured preparation across eight core dimensions. Empirical data collected through surveys and interviews with logistics SMEs inform the framework's development, while real-world case studies present its relevance and applicability. Results demonstrate that the proposed framework is perceived as clearer and more actionable than existing models, especially in guiding decision-makers from minimal readiness toward practical implementation. The study highlights the importance of contextualized guidance, strategic alignment, and operational feasibility in ensuring meaningful ML integration. This research contributes to SME digitalization by offering a scalable and interpretable pathway toward ML adoption in logistics.

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 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. 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 addresses the limitations of the study. Section 7 provides a discussion of the findings. Section 8 concludes the paper. Section 10 contains supplementary material that substantiates the findings of the paper, including case studies, and opens with a glossary.

II. Background Research

A) 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 AI 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. ML 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 ML 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 ML 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 [54]	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 [55]	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 [56]	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 [54]	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 [55]	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 [56]	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. ML 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** [57] 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** [58] 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 with regional laws into readiness evaluation frameworks. Moreover, the **AI Adoption Model for SMEs** by Bettoni et al. [59] offers a practical tool for assessing AI readiness through five key pillars, using qualitative inputs converted into scores from zero to one hundred. Designed for ease of use by non-technical stakeholders, it has been applied to thirty-nine SMEs. While effective for benchmarking, the model lacks a normalization method, limiting cross-study comparability. Adding such a mechanism could support integration with ML readiness models and enhance its analytical utility.

Several frameworks emphasize the technical, infrastructural, and lifecycle dimensions of ML readiness. The **AI Data Readiness Inspector (AIDRIN)** [60] 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** [61] 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** [62] 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** [63] 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** [64] 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** [65] emphasizes internal change capacity, including leadership, innovation culture, and infrastructural maturity. Aligned with this perspective, the **Readiness Model for Artificial Intelligence in Business Enterprises** [66] 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** [67] combines the Technology-Organization-Environment (TOE) [68] and Diffusion of Innovation (DOI) [69] 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 ML 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** [70] 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** [71], 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.

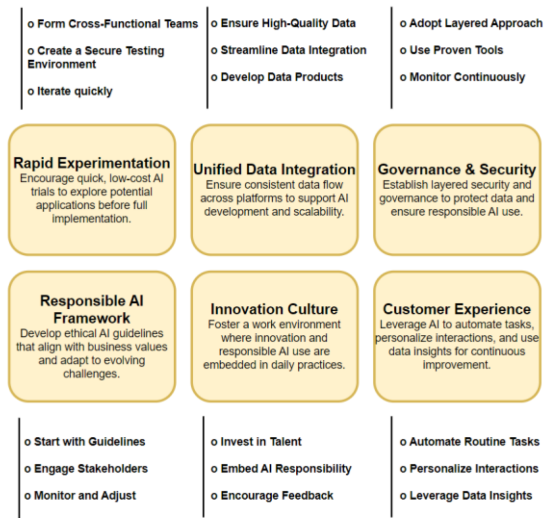


Figure 1 | Potential strategies for SMEs to focus on while preparing for adopting ML / AI

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** [72] 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** [73] proposes a prescriptive, five-phase model (ranging from awareness-building to the development of task-specific 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** [74] 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** [75] 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** [76] 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** [77] 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 six individuals completed the surveys, comprising two 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 ML Preparation & Readiness Assessment for Logistics SMEs (MLPRALS) 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.

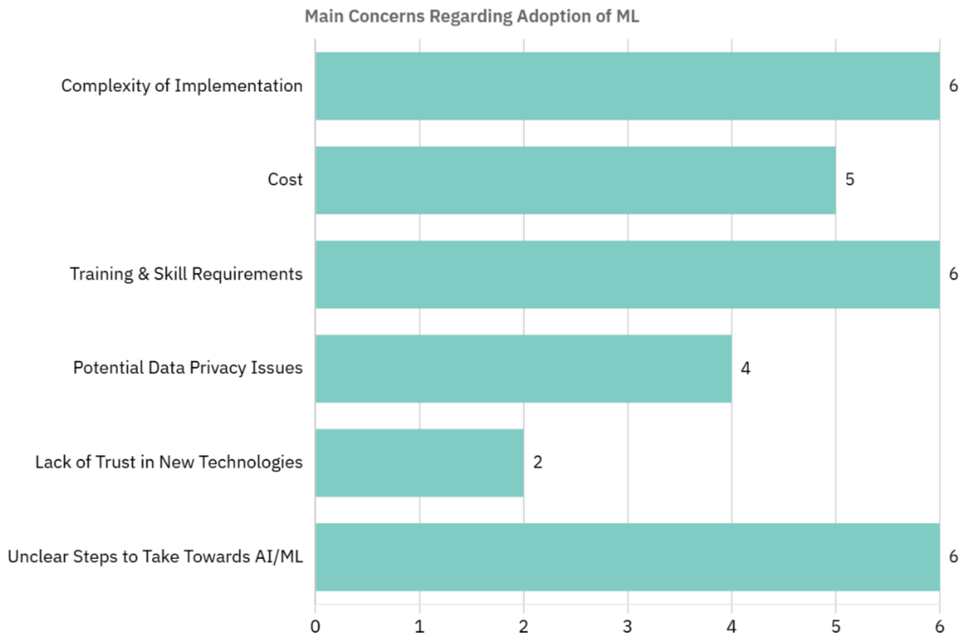


Figure 2 | Survey Responses Regarding Concerns of ML Adoption

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, a shortage of internal expertise necessary for operating advanced IT systems, and a lack of clarity regarding the necessary steps for progressing toward implementation. The surveys also explore prior experiences with technological adoption and the principal concerns expressed by SMEs regarding such transformations, as shown in Figure 2.

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 MLPRALS framework. 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.

Furthermore, a blind survey is conducted following the development of the MLPRALS framework. The survey aims to evaluate the perceived usefulness, clarity, preferability, and contextual suitability of the framework's guidance in comparison to that offered by existing frameworks. The respondents, comprising representatives of logistics SMEs, are presented with eight thematic categories corresponding to the eight readiness and guidance dimensions defined within the MLPRALS framework. Within each category, they are asked to select one of four anonymized guidance statements based on different criteria. To complement the closed-ended responses, each category concludes with an open-ended question designed to capture respondents' rationale for identifying a particular statement as the most appropriate and practically valuable.

To consult the complete structure and full list of the initial survey questions, refer to **section Appendices - Initial Survey Structure**. For the survey questions in the evaluation of guidance across frameworks, consult **section Appendices – Guidance Comparison 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 MLPRALS framework development phase. The insights obtained, in conjunction with a comprehensive literature review on best practices in comparable frameworks, facilitate the design of categories and concepts, specifically tailored to the operational context and constraints of logistics-focused SMEs. They provide 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 readiness assessment function of the MLPRALS 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 instance, 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 the output of prioritized requirements derived from 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 readiness assessment function of the framework.

The MLPRALS framework 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:

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

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) Case Studies

To illustrate the practical applicability of the MLPRALS 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 Logistics SME Framework

Figure 3 provides a visual representation of the proposed categories and associated concepts within MLPRALS 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**.

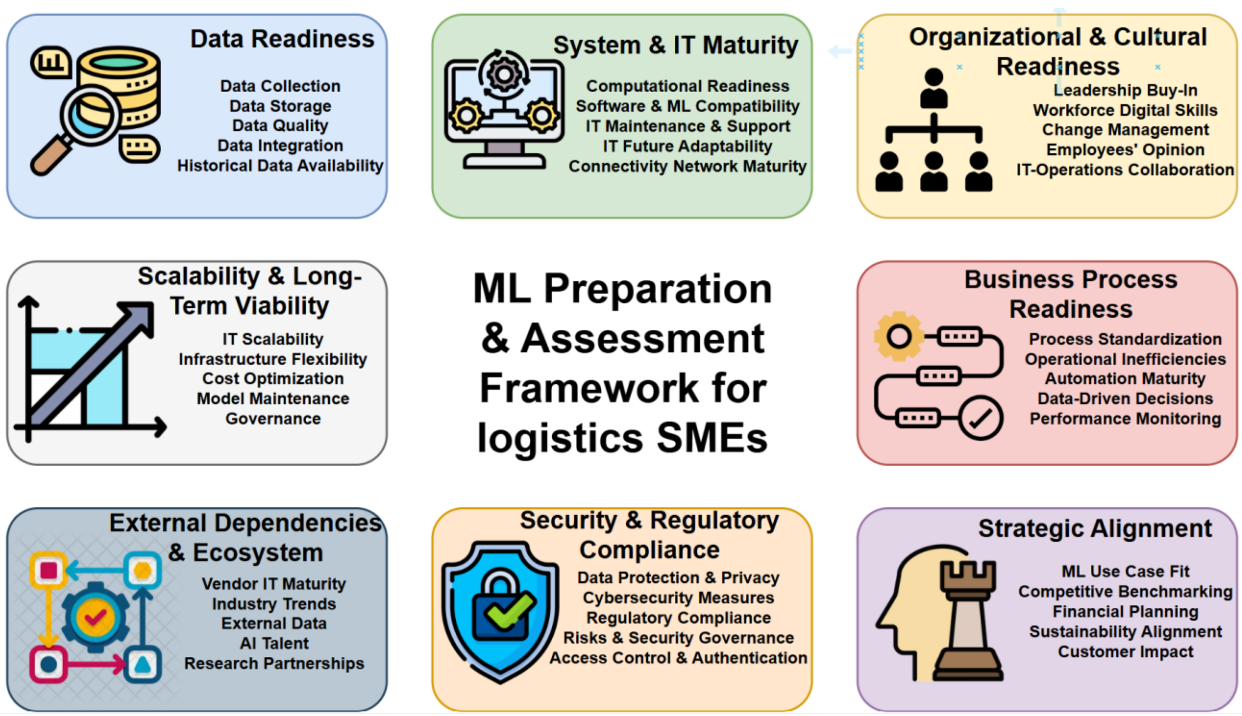


Figure 3 | Visual Representation of Categories and their Concepts in the MLPRALS framework

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), after activities occur. Entry quality and timing are inconsistent.	Data is entered into basic digital tools (e.g., Excel, digital forms), but collection remains manual and scattered across staff and processes.	Key logistics activities (e.g., order intake, inventory changes) are recorded through structured digital systems (e.g., applications, barcode scanners), but input still requires user action.	Data is automatically captured periodically from operational systems (e.g., vehicle tracking, automated workflows), reducing human input and ensuring reliable, consistent records.	Real-time data is collected automatically through connected systems (e.g., IoT, GPS, telematics) 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.

The **Data Readiness Assessment** matrix is presented in Table 5. 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.

The **System & IT Maturity Assessment** matrix is displayed in Table 6. To establish system and IT maturity as a foundation for ML 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 ML 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 ML requirements should be considered when selecting or renewing systems.

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 external troubleshooting when issues arise.	Basic IT support is available but is focused on daily operational software rather than system improvements.	Dedicated IT support (even if external) ensures system stability, updates, and troubleshooting.	IT infrastructure is proactively monitored, ensuring uptime and system optimization.	AI-powered IT maintenance with predictive 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.

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.

The **Organizational & Cultural Readiness Assessment** matrix is outlined in Table 7. 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.

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.

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.

The **Business Process Readiness Assessment** matrix is depicted in Table 8. 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.

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.

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 ML.

The **Strategic Alignment Assessment** matrix is illustrated in Table 9. 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.

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 applies to logistics operations.	Some awareness of ML use cases but not defined strategy for implementation.	Specific ML use cases identified based on business needs (e.g., minimizing errors during manual decision-making).	ML use cases are integrated into logistics strategy with clear performance goals and KPIs.	ML is embedded into core business operations, driving 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.

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.

The **Security & Regulatory Compliance Assessment** matrix is exhibited in Table 10. 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.

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.

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.

The **External Dependencies & Ecosystem Readiness Assessment** matrix is outlined in Table 11. 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.

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 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 ML. 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 ML 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.

The **Scalability & Long-Term Viability Readiness Assessment** matrix is depicted in Table 12. To prepare for the adoption of ML and to ensure it is scalable and long-term viable, logistics SMEs must ensure that ML 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.

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 budget constraints.	Some awareness of ML-related costs, but no structured financial planning for scaling AI solutions.	ML-related costs are assessed, and a cost-effective strategy is in place to support long-term scaling.	Cost analysis optimizes IT investments balancing performance and budget efficiency.	Cost optimization ensures ML models and IT resources scale 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.

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 ML 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 MLPRALS framework to real-world problems, refer to **section Appendices – Case Studies**.

B) Readiness Measurement Across Frameworks

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.

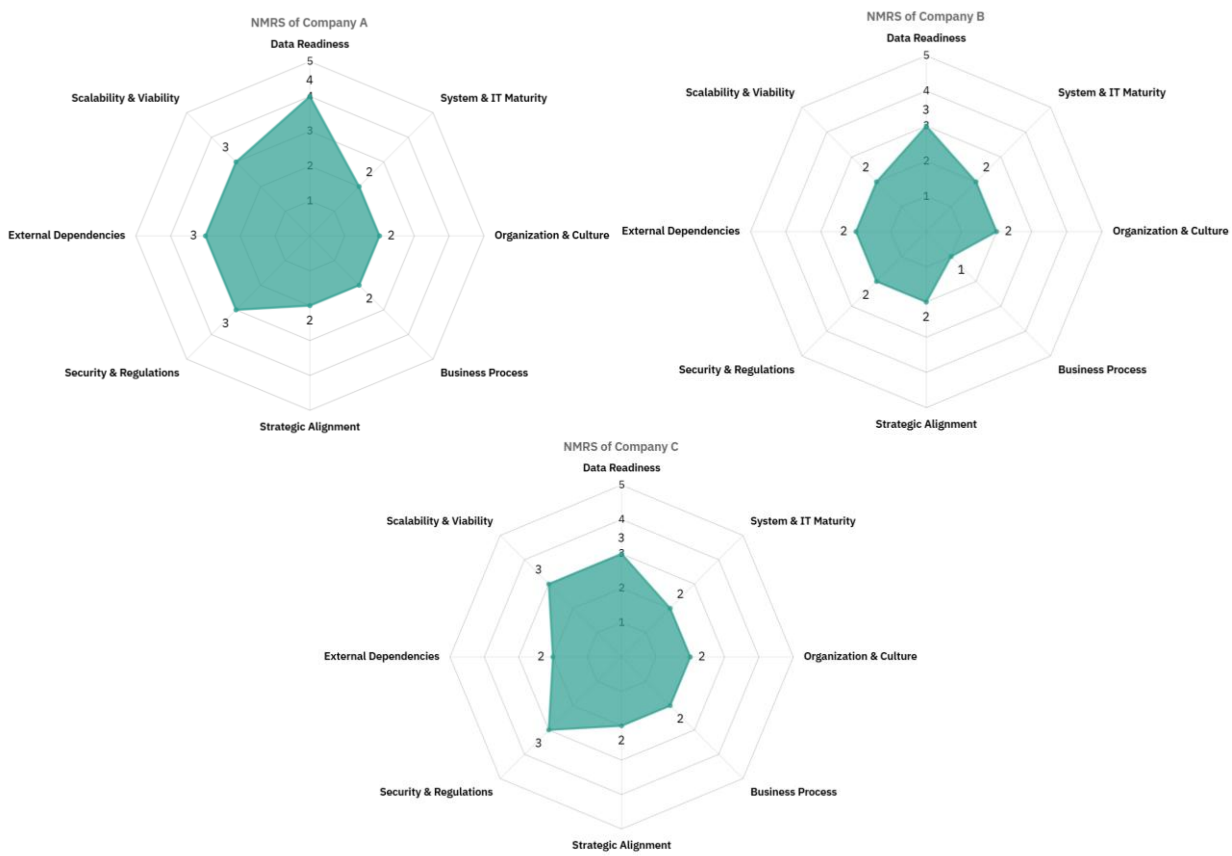


Figure 4 | Normalized ML Readiness Score Across SME Participants

Table 13 | Comparison of Readiness Indexes Across Assessment Frameworks

Framework / Organization	Proposed MLPRALS Framework	Conceptual Framework Model for AI adoption in SMEs [59]	Cisco AI Readiness Index [61]	AI Readiness in Malaysian SMEs Framework [58]	Organizational Readiness Framework [65]
Company A	0.406	0.467	0.33	0.443	0.378
Company B	0.25	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 MLPRALS framework introduced in the study.

For a detailed overview of the results and the normalization of readiness indexes, refer to **section Appendices – Detailed Readiness Index Results**.

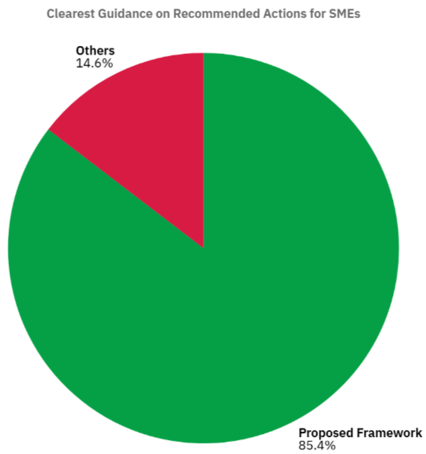
C) Guidance Evaluation

To further validate the proposed framework, its second function is examined. It concerns the provision of guidance tailored to the different levels and categories of ML readiness. A blind survey is conducted to compare the guidance with similar advice from existing AI and ML preparation frameworks.

Figure 5 illustrates that the guidance provided by the proposed framework is generally considered more suitable for logistics SMEs than the guidance drawn from existing frameworks. This is likely due to its direct focus on the needs of this specific type of enterprise. In some cases, however, the results are less conclusive. For example, in Figure 5b, the framework receives less agreement when evaluated for alignment with current SME goals and challenges. This may suggest that SMEs are uncertain about what to improve or how to prepare for ML adoption. It may also indicate that their priorities lie more in logistics operations than in IT-related developments. Despite this, the proposed framework performs more strongly in the other comparison areas.

Another notable result appears in Figure 5f, where respondents are asked to explain in their own words why they consider the proposed framework to be the most useful. The responses are grouped into thematic categories to support interpretation. A key finding is that many of the identified themes correspond directly to gaps highlighted in the existing literature. These include the presence of practical explanations, the consideration of SME-specific constraints, and a clear focus on logistics-sector relevance.

To review the structure and survey questions used in the guidance comparison, refer to **section Appendices – Guidance Comparison Survey Structure**.



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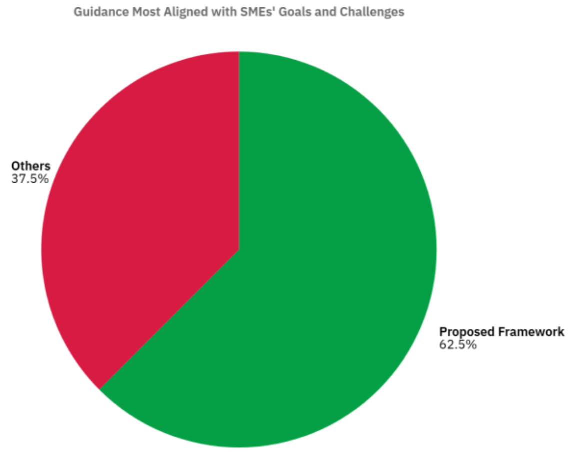

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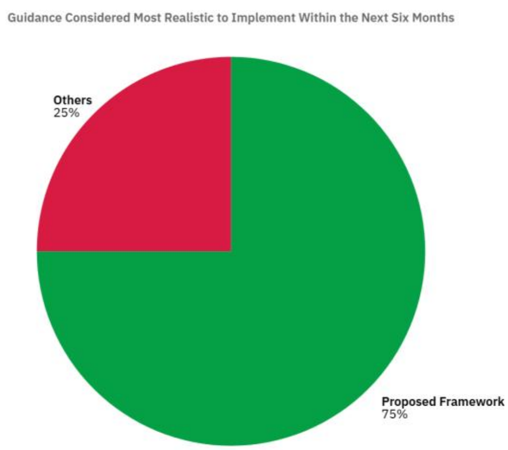

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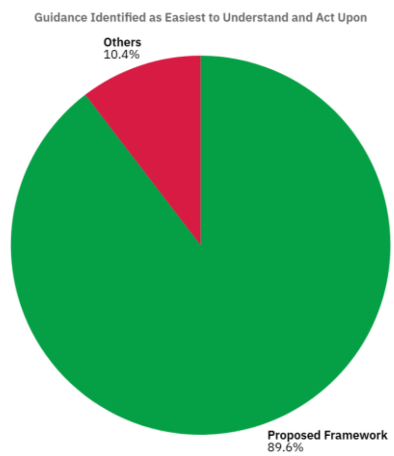

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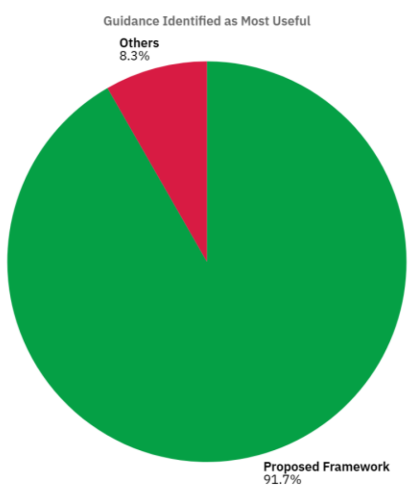

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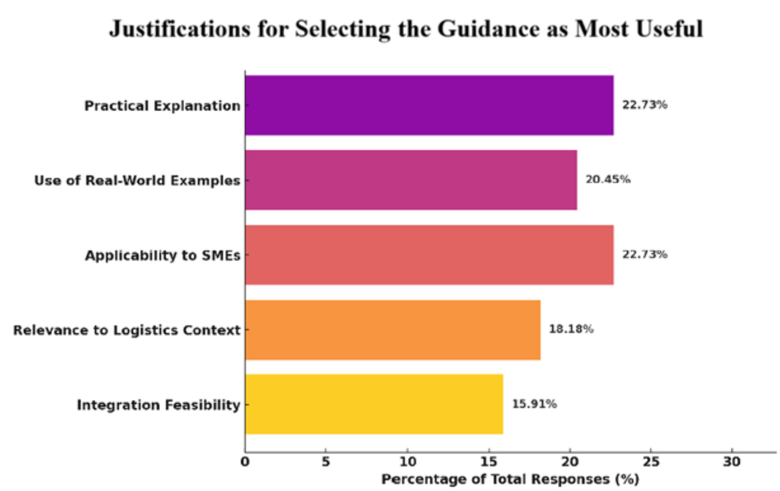

f)

Figure 5 | Guidance Evaluation Survey Results

VII. Limitations

Although the proposed framework demonstrates strong potential for supporting logistics SMEs in their preparation for ML adoption, several limitations must be acknowledged, as they may have influenced the scope and applicability of the study's findings.

A primary limitation lies in the absence of real-world implementation. While the framework addresses concrete challenges identified through interviews and surveys with logistics SME representatives, it has not been applied in an operational setting. This is primarily due to time constraints and the voluntary nature of SME participation. Although the framework's structure, assessment mechanisms, and guidance content are developed based on best practices and validated through empirical input, its application requires full collaboration from a logistics SME. Such involvement is not feasible within the scope of the study, as the participating enterprises maintain different operational priorities. Consequently, the short-term and long-term effects of the framework's application could not be evaluated. Under realistic conditions, observable outcomes would be expected no earlier than six months after adoption for short-term results, and up to two years for long-term impact.

Another limitation concerns the extent to which the proposed framework can be compared to existing frameworks in literature. A comprehensive one-to-one comparison is not feasible, as the reviewed frameworks vary significantly in focus. While some emphasize strategic alignment or sociotechnical guidance, others prioritize technical readiness or organisational and cultural changes. Moreover, many of these frameworks are not tailored to the specific constraints of SMEs, and none address the logistics sector explicitly. As a result, although the proposed framework integrates several of these aspects to address known gaps, the comparison of readiness indexes and guidance effectiveness remains partial.

A final constraint of the study is the limited number of participants involved in the evaluation of the guidance statements. As previously mentioned, the study relies on voluntary engagement, and participation is limited to six individuals across three logistics SMEs. Their willingness to contribute is shaped by time availability and operational priorities, which in turn limit the scale of empirical feedback. To mitigate the constraint, the survey is designed in such a way that each respondent evaluates four different guidance statements across eight distinct readiness categories, using a consistent set of structured questions for each. This design generates a total of forty-eight individual data points per question type, thereby enhancing the depth and reliability of the findings despite the limited number of participants. To ensure consistency, the responses are presented as percentages; however, a larger participant base would enhance the reliability and generalizability of the findings.

VIII. Discussion & Future Work

The strong support for the clarity and perceived usefulness of the proposed framework, as illustrated in Figures 5a, 5d, and 5e, points to a potentially significant insight. The primary barrier to ML adoption among SME decision-makers may not lie in a lack of willingness or concerns regarding implementation complexity, as suggested in Figure 2, but rather in uncertainty and the absence of guidance that is clear, actionable, and tailored to their specific operational context. Furthermore, the high rating for short-term feasibility observed in Figure 5c suggests that SMEs evaluate potential frameworks not only in terms of strategic alignment, but also according to their capacity to deliver tangible results within limited timeframes and resources. Taken together, these findings indicate that ML readiness in SMEs should be understood not solely as a technical or procedural state, but also as an interpretive process. Effective guidance must not only identify gaps but also contextualize them and translate recommendations into sector-relevant strategies that SMEs can realistically implement.

This interpretation is further supported by qualitative insights obtained through interviews and surveys, revealing that intuition-based decision-making remains the biggest limitation within logistics SMEs, despite the availability of sufficient data to support analytical processes. This issue presents itself differently across the three participating companies, depending on their operational focus. One enterprise experiences understocking due to cautious purchasing practices aimed at limiting costs and storage use, while another faces overstocking challenges resulting from the perishability of goods. The third company encounters inefficiencies in transport and route planning, which negatively affect delivery reliability and customer satisfaction. Although the underlying cause is consistent, the operational impact differs according to each firm's structure and priorities.

In response to these findings, the proposed MLPRALS framework supports logistics SMEs in preparing for the adoption of ML solutions that match their specific needs. Its structure allows for flexible application across diverse operational functions, while also accommodating SMEs of varying sizes. Among the participants, company sizes range from fewer than 50 employees to nearly 250, with activities spanning domestic warehousing, reverse logistics, and international distribution. Despite these differences, the results presented in Figure 5 confirm that all three companies consider the proposed framework the most suitable for their context, indicating its ability to generalize while remaining sensitive to organisational variation.

In comparison to established frameworks [57, 58, 60, 63, 64, 65, 66, 67, 71, 72], the findings of this study highlight the importance of providing not only recommendations on what should be done, but also clear justification and guidance on how and why specific actions are advised. This approach is shown to be more effective in helping SME decision-makers develop a deeper understanding of their current limitations and identify targeted pathways for improvement. Such clarity enhances their ability to derive greater value from ML adoption.

Moreover, existing frameworks often provide guidance under the assumption that companies are already at a baseline level of readiness for ML adoption. By contrast, the proposed framework is designed to support enterprises beginning from minimal or no readiness, progressing toward full preparedness and beyond. Furthermore, the majority of ML and AI preparation frameworks are developed with larger organizations in mind. Few are tailored specifically to SMEs, even fewer address the logistics sector, and none focus explicitly on the unique needs of logistics-oriented SMEs. In addition, most frameworks found in existing literature do not provide a formal readiness index, limiting measurable self-assessment when compared to the structured scoring approach introduced in the proposed MLPRALS framework.

The study contributes practically by demonstrating the feasibility of integrating readiness assessment with actionable guidance to support SME decision-makers in understanding their current position and progression toward technological advancement. Theoretically, it affirms the need for a sector-specific framework tailored to the logistics domain, as the findings indicate that existing frameworks are not well-suited to the distinct challenges and operational characteristics of logistics SMEs. Methodologically, the study underscores the importance of comprehensive guidance that addresses multiple readiness dimensions, rather than focusing on isolated aspects such as technical capability or sociopsychological adaptation, to ensure that SMEs can derive maximum value from ML adoption.

Future research should focus on applying the framework in a real-world logistics environment. While its development is informed by input from logistics SMEs, operational testing remains unaddressed. Collaboration with an enterprise willing to integrate the framework would allow for the observation of short-term and long-term measurable outcomes over time.

The framework may also be adapted for use in other SME sectors. Its structure and assessment logic can be adjusted to reflect the specific challenges of industries such as manufacturing, retail, or healthcare. Exploring this potential would contribute to broader SME readiness for ML adoption.

IX. Conclusion

This study proposes a structured, context-specific, and modular framework to support logistics-oriented SMEs in assessing and enhancing their readiness for ML adoption. The MLPRALS framework is developed based on an extensive literature review, a comparative analysis of existing readiness and preparation models, and empirical data collected through surveys and interviews with logistics SMEs.

The proposed framework distinguishes itself by providing not only prescriptive recommendations, but also explicit rationales and detailed procedural guidance for the implementation of advised actions. It addresses the particular resource limitations and operational challenges faced by logistics SMEs, combining readiness assessment and preparatory guidance within a single model. Covering eight critical dimensions of readiness, it provides a more comprehensive and practically oriented approach than existing frameworks, which often focus narrowly on technical or organizational factors.

The findings demonstrate that the framework aligns with the operational realities of logistics SMEs and is perceived as clearer and more useful than existing AI / ML preparation models. They further highlight that effective ML adoption requires not only technical capability but also contextualization, interpretability, and strategic integration into business processes. Through its sectoral focus, empirical foundation, and multidimensional structure, the study advances the discourse on SME digitalization and ML readiness. Future research should validate the framework through longitudinal application in operational environments and examine its applicability in other industries where SMEs predominate.

X. References

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XI. Appendices

A) Glossary

Table 14 | Glossary Table

Term	Definition
AI	Artificial Intelligence (the simulation of human intelligence in machines that are programmed to think, learn, and make decisions)
API	Application Programming Interface (a set of rules that allows different software systems to communicate with each other)
ARIMA	AutoRegressive Integrated Moving Average (a statistical model used for time series forecasting by analyzing differences between values)
ERP	Enterprise Resource Planning (integrated management software used to collect, store, manage, and interpret data in businesses)
GDPR	General Data Protection Regulation (a legal framework that sets guidelines for the collection and processing of personal data in the European Union)
IoT	Internet of Things (a system of interrelated devices connected to the internet that collect and exchange data)
KPI	Key Performance Indicator (a measurable value used to evaluate the success of an organization or of a particular activity)
LSTM	Long Short-Term Memory (a type of recurrent neural network (RNN) capable of learning long-term dependencies in sequential data)
ML	Machine Learning (a subset of AI that enables systems to learn from data and improve their performance without being explicitly programmed)
SAP	Systems, Applications, and Products in Data Processing (a multinational software corporation known for its enterprise resource planning)
SME	Small and Medium-sized Enterprise (a business entity with a limited number of employees and turnover, defined differently across regions)
TMS	Transportation Management System (software that facilitates the planning, execution, and optimization of the physical movement of goods)
VPN	Virtual Private Network (a secure connection method used to add privacy and security to private and public networks)
WMS	Warehouse Management System (software applications that support the day-to-day operations in a warehouse)

B) Challenges in 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 6, including energy-efficient technologies, optimized transport routes, and alternative fuels, to comply with environmental regulations while improving efficiency and cost savings [78]. 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 [79].

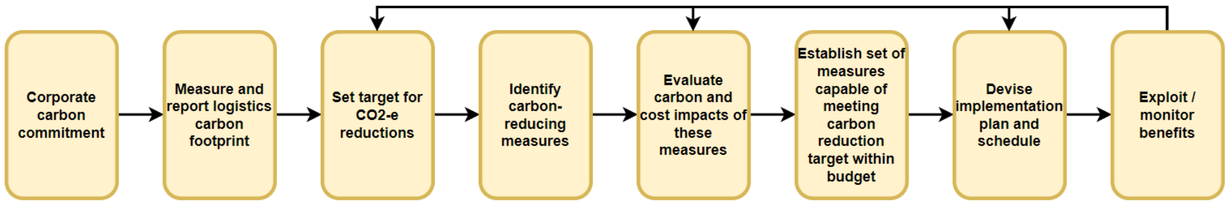

Figure 6 | Stages in the development of a decarbonization strategy for logistics

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 [80]. 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 [81].

AI and predictive analytics enhance demand forecasting, inventory management, and route efficiency, reducing costs and optimizing deliveries [82, 83]. Blockchain and digital freight platforms improve transparency and automate transactions, optimizing freight matching and reducing inefficiencies [84].

Sustainability initiatives, including electric vehicles and renewable energy, are shaping the future of logistics alongside geopolitical risks that require adaptive supply chain strategies [85]. Venture capital investments in autonomous delivery, AI logistics, and digital platforms continue to drive industry innovation [86]. 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 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 [87]. 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 [88].

Meta-learning and multi-task learning facilitate adaptive supply chain management, particularly in shipping cost prediction, by enabling rapid adaptation with limited data [89]. Reinforcement learning has optimized urban logistics, improving last-mile delivery efficiency through a hybrid Q-learning algorithm [90]. Self-supervised learning enhances damage-avoidance strategies, refining autonomous handling of fragile goods without human intervention [91]. Semi-supervised learning addresses data scarcity challenges, combining labeled and unlabeled data to improve inventory prediction and demand forecasting [92].

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 [93]. These findings underscore ML'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 ML 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 [94].

Security vulnerabilities, including adversarial attacks designed to manipulate AI models, threaten the integrity of ML 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 [95].

Ethical concerns extend to bias, accountability, and transparency. ML 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 [96]. 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 ML practices [97].

E) Additional ML information

Tables 15 and 21 illustrate the comparison of supervised, unsupervised, and federated learning across different criteria (technical and non-IT important factors). Supervised, unsupervised, and federated learning represent foundational ML paradigms, each offering distinct capabilities and limitations depending on the context and data availability. Supervised learning relies on labeled datasets to train models that map inputs to outputs, achieving high performance in classification and regression tasks. It is widely used in domains such as healthcare diagnostics, fraud detection, speech recognition, autonomous driving, and email filtering. However, its dependence on extensive labeled data, vulnerability to overfitting, and computational demands pose practical constraints.

Unsupervised learning, by contrast, operates without labeled data, extracting latent patterns, clusters, or anomalies through statistical and distance-based techniques. It is valuable for exploratory analysis in domains such as marketing segmentation, anomaly detection in finance, medical imaging, and recommendation systems. Although it reduces annotation costs and enables discovery of hidden structures, interpretability and evaluation remain challenging, with model tuning often requiring iterative experimentation and indirect validation methods.

Federated learning introduces a privacy-preserving, decentralized alternative that allows model training across distributed devices without centralizing raw data. This approach is particularly relevant in regulated or privacy-sensitive environments such as mobile applications, healthcare, and financial services. While it reduces data transfer and strengthens user privacy, it also introduces challenges related to communication latency, and hardware heterogeneity against adversarial interference. Its implementation necessitates secure aggregation protocols and consistent model synchronization using algorithms such as Federated Averaging and Federated SGD.

Table 15 | Technical Evaluation Supervised Learning, Unsupervised Learning, Federated Learning

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
Supervised Learning [98]	High performance when sufficient labeled data is available, making it reliable for classification and regression tasks.	Efficient with small datasets but computationally intensive with large-scale training.	This method relies heavily on large, labeled datasets for optimal performance. Its efficiency decreases significantly when data is sparse or labels are inconsistent.	Offers moderate interpretability, particularly with linear models and decision trees. Complex architectures, such as deep neural networks, reduce explainability.	Adaptability is task-specific, with significantly reduced transferability to divergent tasks, often necessitating retraining.	Susceptible to bias when training data is imbalanced or reflects societal inequalities. Ethical concerns arise when predictions influence decision-making.	Implementation costs depend on data availability and labeling requirements, with higher expenses for large datasets.	Vulnerable to adversarial manipulation, particularly for deep learning models.
Unsupervised Learning [99]	Performance varies depending on data quality and clustering algorithms used, often less precise than supervised methods.	Efficient for simple clustering but becomes complex with high-dimensional data.	It depends on the availability of sufficient unlabeled data, with efficiency highly influenced by the quality and distribution of the dataset.	Interpretation remains challenging due to the absence of labeled outputs. Cluster analysis can provide insights, though results often lack transparency.	Adaptability is influenced by data quality and structure; general techniques perform poorly on distributionally distinct datasets.	Ethical risks include biased clustering outcomes, particularly when demographic features dominate feature space.	Moderate implementation costs, though complex clustering algorithms increase computational expenses.	Susceptible to perturbations that alter clustering and anomaly detection outcomes.
Federated Learning [100]	Accuracy comparable to centralized training when data is balanced across devices, though performance degrades with heterogeneity.	Efficiency depends on communication overhead between devices and the central server.	Data remains distributed across devices, requiring balanced datasets for optimal performance. Heterogeneous data reduces sample efficiency.	Model updates can be interpreted similarly to centralized learning, though privacy-preserving mechanisms may obscure detailed insights.	Adaptability is moderate in decentralized settings, while transferability is limited by data heterogeneity across devices.	Enhances privacy but complicates bias detection due to decentralized training.	Increased infrastructure costs for decentralized training, though implementation remains feasible with cloud platforms.	Decentralization increases vulnerability to model poisoning attacks.

Tables 16 and 22 illustrate the comparison of distributed, transfer, and self-supervised learning across different criteria (technical and non-IT important factors). Distributed, transfer, and self-supervised learning represent advanced ML approaches that address scalability, efficiency, and data availability constraints in modern applications. Distributed learning enables parallel model training across multiple computing nodes, significantly accelerating training time and improving system resilience. This approach is employed in large-scale deep learning tasks, including recommendation systems, scientific simulations, and financial analytics. However, challenges arise from communication overhead, hardware heterogeneity, and the complexity of coordination, often necessitating expertise in parallel computing.

Transfer learning improves efficiency by reusing knowledge from pre-trained models to solve new, related tasks with minimal data. Commonly applied in domains such as natural language processing, computer vision, and autonomous systems, it reduces the demand for large, annotated datasets and accelerates development. Implementation involves careful fine-tuning, access to structurally compatible pre-trained models, and appropriate use of techniques such as layer freezing and feature extraction. Nonetheless, transfer learning is sensitive to the compatibility between source and target domains. Mismatches can result in negative transfer, and inherited biases from the original training data may compromise performance in new contexts.

Self-supervised learning addresses the limitations of labeled data by creating supervisory signals from the data itself. It constructs auxiliary tasks, enabling models to learn useful representations from raw inputs. This method is increasingly used in text understanding, image analysis, medical imaging, and autonomous navigation. While it offers strong generalization and scalability, its success depends on the design of effective pretext tasks, access to large-scale data, and substantial computational resources. Evaluation of learned representations remains complex, as conventional metrics often fail to capture representation quality, and indirect supervision may introduce latent biases.

Table 16 | Technical Evaluation Distributed, Transfer, and Self-Supervised Learning

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
Distributed Learning [101]	High accuracy achieved through parallel training, provided data distribution is balanced, and models are properly synchronized.	Enhances efficiency through parallel processing but increases complexity due to synchronization requirements.	Efficiency depends on balanced data distribution across nodes, as uneven datasets can lead to convergence issues and inconsistent model performance.	Interpretability aligns with the base model but decreases when complex synchronization and ensemble methods are employed.	Adaptability depends on data partitioning strategies. Transferability between environments remains challenging unless models are designed to accommodate data shifts.	Ethical risks align with the base models, though distributed environments complicate bias monitoring.	High costs due to infrastructure and synchronization requirements, limiting feasibility for resource-constrained environments.	Attack surfaces expand with increased model communication across nodes.
Transfer Learning [102]	Strong performance when pre-trained models are adapted to similar tasks, with accuracy decreasing as task divergence increases.	Efficient when leveraging pre-trained models but resource-intensive during initial training.	Requires significantly fewer samples for target tasks when pre-trained on large datasets, enhancing efficiency for new tasks with limited data.	Moderate explainability, as pre-trained models often inherit interpretability limitations from the original training task.	Designed for high adaptability, particularly when source and target tasks share similar features. Transferability degrades with increasing divergence between tasks.	Bias can transfer from pre-trained models, particularly when source and target domains differ demographically.	Reduces costs by leveraging pre-trained models, though fine-tuning expenses increase with task divergence.	Adversarial vulnerabilities transfer from pre-trained models.
Self-Supervised Learning [103]	Effective for feature extraction and pre-training, though final accuracy depends on downstream task fine-tuning.	Computationally demanding during pre-training but efficient for downstream tasks.	Relies on large, unlabeled datasets for pre-training. Once trained, downstream tasks achieve high efficiency with minimal labeled data.	Interpretation remains challenging due to the unsupervised nature of pre-training, though downstream models can enhance transparency.	Adaptive across various tasks due to strong feature extraction capabilities. Transferability improves for downstream tasks after pre-training.	Ethical concerns arise when unlabeled data contains biases that propagate through pre-trained models.	High initial training costs, though downstream applications become cost-effective.	Powerful during pre-training but susceptible during downstream fine-tuning.

Table 17 | Technical Evaluation Meta, Multi-Task, and Semi-Supervised Learning

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
Meta-Learning [104]	High performance for few-shot tasks, though it may underperform when training data is abundant.	Efficient for new task adaptation but resource-intensive during meta-training.	Achieves high sample efficiency by leveraging knowledge from prior tasks. Performance declines when applied to tasks significantly different from training data.	Provides limited interpretability, as models focus on rapid adaptation rather than understanding task-specific decision-making.	Prioritizes adaptability by training models to generalize quickly to new tasks with minimal data. Transferability weakens for tasks outside the original problem domain.	Ethical risks increase when rapid adaptation reinforces existing biases without sufficient oversight.	Expensive during meta-training, though task-specific adaptation remains feasible.	Susceptible to attacks on base tasks and rapid adaptation processes.
Multi-Task Learning [105]	Enhanced accuracy when tasks share underlying features but can degrade if tasks conflict.	Efficiency depends on task similarity, with increased complexity for diverse tasks.	Efficiency improves when tasks share common features, though divergent tasks increase data requirements and reduce overall performance.	Interpretation becomes complex when tasks conflict, though shared feature representations can enhance transparency.	Enhances adaptability when tasks share common features but reduces transferability if task-specific conflicts arise.	Bias can propagate across tasks, particularly when dominant tasks influence shared feature representations.	Implementation costs rise with task complexity and potential conflicts.	Vulnerabilities increase when task conflicts arise.
Semi-Supervised Learning [106]	Achieves near-supervised accuracy when a small amount of labeled data complements large unlabeled datasets.	Efficient with limited labeled data but computationally demanding for large unlabeled datasets.	Requires fewer labeled samples by leveraging large quantities of unlabeled data. Efficiency decreases when unlabeled data introduces noise.	Interpretability aligns with supervised learning, though the inclusion of unlabeled data complicates understanding model decisions.	Moderate adaptability when labeled and unlabeled datasets share similar distributions. Transferability remains limited outside the initial training context.	Ethical concerns arise when unlabeled data introduces biases into decision-making processes.	Reduces labeling costs but increases computational expenses for iterative training.	Susceptible to attacks through manipulated unlabeled data.

Tables 17 and 23 illustrate the comparison of meta, multi-task, and semi-supervised learning across different criteria (technical and non-IT important factors). Meta-learning, multi-task learning, and semi-supervised learning represent advanced approaches that address limitations in data availability, adaptability, and learning efficiency across diverse ML contexts. Meta-learning, also referred to as “learning to learn,” focuses on improving models' ability to generalize across tasks by leveraging prior experiences. It is particularly effective in few-shot scenarios where data is scarce and fast adaptation is essential. Common applications include robotics, personalized healthcare, multilingual natural language processing, and automated model selection in AutoML. Effective implementation depends on access to diverse task distributions, the use of algorithms such as MAML or memory-augmented networks, and benchmarking strategies. Challenges include high computational demands, overfitting to meta-training tasks, and the complexity of evaluating generalization performance.

Multi-task learning trains a single model to perform several related tasks simultaneously, allowing the model to share feature representations and improve overall efficiency. This approach is widely used in natural language processing, computer vision, speech recognition, and recommender systems, where learning multiple objectives jointly enhances performance. Key requirements include datasets annotated for multiple tasks, neural architectures that combine shared and task-specific components, and optimization techniques that balance competing learning signals. Although this method improves generalization and reduces model redundancy, it requires careful management of conflicting objectives and task weightings, along with adequate computational resources.

Semi-supervised learning combines the strengths of supervised and unsupervised approaches, using a small, labeled dataset alongside a large volume of unlabeled data to improve model performance. It is applied in areas where labeling is expensive or time-consuming, such as medical imaging, speech processing, cybersecurity, and autonomous driving. Implementation involves algorithms like self-training, label propagation, and consistency regularization, and relies on the assumption that labeled and unlabeled data originate from similar distributions. The approach reduces annotation costs and improves generalization but carries risks related to pseudo-labeling errors, distribution mismatch, and the need for fine-grained hyperparameter tuning.

Tables 18 and 24 illustrate the comparison of privacy-preserving, active, and ensemble learning across different criteria (technical and non-IT important factors). Privacy-preserving learning, active learning, and ensemble learning represent specialized ML paradigms designed to address critical challenges in data security, annotation efficiency, and model performance. Privacy-preserving learning focuses on enabling model training without compromising sensitive information, using techniques such as differential privacy, homomorphic encryption, and secure multi-party computation. This approach is particularly relevant in regulated domains such as healthcare, finance, and biometric authentication, where data confidentiality is legally and ethically required. Implementation demands cryptographic expertise, secure aggregation methods, and compliance with privacy regulations. While these methods enhance security and foster cross-institutional collaboration, they introduce computational overhead and may reduce model accuracy due to noise injection and encryption constraints.

Table 18 | Technical Evaluation Privacy-Preserving, Active, and Ensemble Learning

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
Privacy-Preserving Learning [107]	Performance remains close to traditional methods if privacy-preserving mechanisms do not excessively perturb data.	Efficiency depends on the complexity of privacy-preserving mechanisms.	Data dependency increases when privacy-preserving mechanisms, such as differential privacy, introduce noise into the training process.	Reduces interpretability due to noise introduction and encrypted computations, complicating model transparency.	Adaptability decreases with stricter privacy constraints. Transferability across platforms remains challenging due to encryption and noise.	Enhances data privacy but complicates bias detection and mitigation due to encrypted computations.	Higher costs due to encryption and differential privacy mechanisms.	Enhanced resilience through encryption but vulnerable to side-channel attacks.
Active Learning [108]	High accuracy achieved with fewer labeled samples, as the model focuses on informative examples.	Reduces labeling effort but increases computational complexity for sample selection.	Improves sample efficiency by prioritizing the most informative data points for labeling, thereby reducing overall labeling requirements.	Enhances interpretability by focusing on informative samples, though model explanations remain task dependent.	Adaptive in prioritizing data for labeling but lacks transferability to entirely new tasks without retraining.	Reduces bias by prioritizing diverse data samples for labeling, though biased query strategies can undermine this advantage.	Reduces labeling costs but increases computational expenses for query strategies.	Adversarial queries can manipulate the sample selection process.
Ensemble Learning [109]	Combines multiple models to achieve superior accuracy compared to individual learners.	Enhances efficiency through model combination but increases resource consumption.	Requires more data for training multiple models but improves efficiency through model diversity and voting mechanisms.	Reduces interpretability due to model aggregation, though individual learners may remain explainable.	Adaptability improves through model diversity, though transferability remains dependent on the individual learners.	Bias persists if base models reflect discriminatory patterns, though model diversity can mitigate bias to some extent.	High implementation costs due to multiple model training and deployment.	Increased resilience through model diversity but remains vulnerable if base learners are compromised.

Active learning addresses the inefficiencies associated with manual annotation by enabling models to selectively query the most informative data points for labeling. It is widely applied in domains such as medical imaging, sentiment analysis, autonomous driving, and fraud detection, where annotation costs are high. By focusing human input on uncertain or edge-case instances, active learning improves data efficiency and accelerates model refinement. Effective deployment requires uncertainty sampling strategies, human-in-the-loop infrastructures, and continuous model retraining. Although it reduces annotation costs, it increases system complexity and computational load, and its performance depends heavily on the effectiveness of the query strategy employed.

Ensemble learning enhances predictive robustness and generalization by combining multiple models. Techniques such as bagging, boosting, and stacking aggregate diverse model outputs to improve stability and accuracy across complex datasets. It is broadly applied in financial risk modeling, medical diagnostics, fraud detection, recommendation systems, and weather forecasting. Ensemble learning requires careful selection of complementary base models and efficient aggregation mechanisms such as majority voting or weighted averaging. The benefits include improved accuracy, resilience to noise, and flexibility in integrating various model types. However, the approach increases computational demands, complicates interpretability, and may yield diminishing returns with additional model complexity.

Tables 19 and 25 illustrate the comparison of generative, few-shot and zero-shot, and contrastive learning across different criteria (technical and non-IT important factors). Generative learning, few-shot and zero-shot learning, and contrastive learning represent cutting-edge approaches in ML that address challenges related to data scarcity, generalization, and representation learning. Generative learning focuses on modeling the underlying distribution of data to generate new, realistic samples. It is used in domains such as image synthesis, text generation, data augmentation, and drug discovery, employing methods like generative adversarial networks (GANs), variational autoencoders (VAEs), and normalizing flows. Effective implementation requires large, high-quality datasets, sophisticated model architectures, and computationally intensive training procedures. While generative models support creativity, data augmentation, and robustness, they present limitations related to training complexity, limited interpretability, and ethical concerns in applications such as misinformation and deepfake generation.

Few-shot and zero-shot learning aim to enable models to generalize to new tasks with minimal or no labeled examples. Few-shot learning adapts to novel categories using only a small number of samples, while zero-shot learning leverages semantic embeddings to recognize unseen classes without direct training. Implementation requires access to pre-trained models, meta-learning algorithms such as MAML, and semantic linkage methods like word vectors. Although these approaches reduce dependence on large, annotated datasets and support fast deployment, they are sensitive to input variability and require careful regularization to prevent overfitting. Semantic misalignment in zero-shot learning may result in poor generalization when unseen classes diverge from prior knowledge.

Contrastive learning is a representation learning technique that trains models to distinguish between similar and dissimilar instances by organizing them in a latent feature space. It is especially useful in self-supervised settings where labeled data is limited, with applications in computer vision, text similarity, medical imaging, anomaly detection, and recommendation systems. This method relies on data augmentation strategies to create sample pairs and employs contrastive loss functions such as InfoNCE to optimize representation quality. The advantages of contrastive learning include strong generalization, transferability to downstream tasks, and improved interpretability of model outputs.

Table 19 | Technical Evaluation Generative, Few-Shot and Zero-Shot, Contrastive Learning

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
Generative Learning [110]	Effective for generating realistic data, though accuracy depends on model architecture and training stability.	Computationally intensive, particularly with complex architectures like GANs.	Efficient at generating new data samples after training but initially demands substantial datasets for effective learning.	Interpretation remains challenging, particularly with complex architectures like GANs. Generated outputs can obscure underlying decision-making processes.	Adaptive for data generation tasks but transferability decreases when applied to domains outside the training distribution.	Ethical risks include generating biased or harmful content if training data lacks diversity.	Expensive for complex architectures but feasible for data augmentation.	Vulnerable to adversarial examples that disrupt data generation.
Few-Shot and Zero-Shot Learning [111]	Accuracy depends heavily on the quality of the training examples and task similarity.	Efficient for inference but demanding during model training.	Highly sample-efficient, with the ability to generalize from minimal training data. Performance depends heavily on task similarity.	Limited interpretability, as model generalization relies heavily on abstract feature representations.	Designed for high adaptability and transferability, though task similarity remains a critical factor.	Bias can transfer from pre-trained models, particularly when training examples reflect societal inequalities.	Cost-effective for downstream tasks but expensive during initial model development.	Susceptible to adversarial inputs due to limited training samples.
Contrastive Learning [112]	Effective for representation learning, enhancing downstream task accuracy.	Increases training complexity but enhances efficiency for downstream tasks.	Relies on large datasets for pre-training but enhances sample efficiency for downstream tasks through effective feature learning.	Improves interpretability by enhancing feature representation, though decision-making paths remain opaque.	Enhances adaptability through feature representations but reduces transferability when the feature space changes significantly.	Ethical concerns include biased representations when positive and negative samples reflect demographic imbalances.	Higher training costs but feasible for downstream applications.	Vulnerable to perturbations that alter positive and negative sample relationships.

Tables 20 and 26 illustrate the comparison of Explainable AI (XAI), Neural Architecture Search (NAS), and Multi-Modal learning across different criteria (technical and non-IT important factors). XAI, NAS, and Multi-Modal Learning represent advanced ML paradigms that address transparency, model design automation, and multi-source data integration. XAI focuses on enhancing interpretability by offering human-understandable explanations for model predictions. It is essential in high-stakes fields such as healthcare, finance, and legal analytics, where transparent decision-making improves trust, ensures compliance, and supports human-AI collaboration. Implementation relies on interpretability tools such as SHAP, LIME, and counterfactual reasoning, and often balances trade-offs between accuracy and transparency. Despite its benefits, XAI faces challenges in simplifying complex models without distorting their underlying behavior, and explanation methods may not always align with actual model logic, risking misleading interpretations.

NAS automates the discovery of optimized neural network architectures by exploring a large space of structural configurations using search strategies such as reinforcement learning, evolutionary algorithms, and gradient-based optimization. It has shown significant success in image classification, natural language processing, and edge computing, allowing for the creation of domain-specific and resource-efficient models. NAS accelerates innovation and reduces dependence on manual trial-and-error design, but it is computationally expensive and may produce architectures that are difficult to interpret or transfer to new tasks. Reproducibility and generalization also remain concerns, especially when models are overfitted to benchmark datasets during the search process.

Multi-modal learning enables models to process and integrate multiple data modalities, such as text, images, audio, and sensor signals, within a single framework. It is widely used in autonomous vehicles, virtual assistants, medical diagnostics, and video understanding. The approach enhances contextual awareness by leveraging complementary information across modalities. Implementation requires access to multi-modal datasets, specialized fusion strategies, and architectures such as cross-attention networks and multi-modal transformers. Although multi-modal learning improves generalization and supports complex perception tasks, it introduces significant computational overhead and challenges in aligning heterogeneous data. The risk of modality imbalance and the scarcity of annotated multi-modal datasets further complicate development and scalability.

Table 20 | Technical Evaluation Explainable AI, Neural Architecture Search, Multi-Modal Learning

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
Explainable AI (XAI) [113]	Accuracy aligns with underlying models but may slightly decrease when interpretability constraints are applied.	Reduces efficiency when explainability constraints increase model complexity.	Efficiency aligns with the underlying model but may decrease when interpretability constraints limit model complexity.	Prioritizes interpretability by design, ensuring that model decisions can be understood and validated by human stakeholders.	Adaptability depends on the underlying model's flexibility. Transferability may decline when explainability constraints limit model complexity.	Enhances ethical accountability by increasing transparency, though trade-offs with model complexity may arise.	Implementation remains feasible, though interpretability constraints can increase costs.	Enhanced resilience through transparent decision-making but remains susceptible to underlying model vulnerabilities.
Neural Architecture Search (NAS) [114]	High accuracy achieved by optimizing architecture, though computational intensity can limit effectiveness.	Highly complex due to iterative search and evaluation.	Data dependency increases with the complexity of architecture search, though sample efficiency improves when optimized architectures are identified.	Reduces explainability due to the complexity of search algorithms and resulting architectures.	Adaptive to task-specific architecture requirements but less transferable without re-running the search process.	Ethical risks remain tied to the underlying architectures, with limited bias mitigation during search.	High implementation costs due to iterative search processes.	Vulnerable to adversarial architectures unless search processes prioritize safety.
Multi-Modal Learning [115]	Strong performance when integrating multiple data sources, though imbalanced modalities can reduce accuracy.	Efficiency depends on balanced data streams and model architecture.	Requires balanced datasets across modalities. Efficiency decreases when one modality dominates or when data is missing from a specific source.	Interpretation becomes challenging when combining multiple data sources, as feature interactions may lack transparency.	Adaptive when modalities remain consistent but less transferable when new modalities are introduced or when data imbalances occur.	Biases can propagate across modalities, particularly when dominant data sources reflect societal inequalities.	Expensive when integrating multiple modalities, particularly with imbalanced datasets.	Attack surfaces expand with increased modality integration.

Table 21 | Non-IT SME Important Factors Supervised, Unsupervised, Federated Learning

ML / Criteria	Ease of Implementation and Integration	Data Availability and Quality	Transparency and Explainability	Operational Impact and Workflow Integration	Support and Maintenance	Risk Management and Data Privacy	Scalability and Futureproofing	User-Friendliness and Training Requirements
Supervised Learning [98]	Implementation remains straightforward when labeled datasets are available, with seamless integration into existing workflows using established libraries and frameworks.	Performance depends heavily on the availability of large, labeled datasets. Data quality significantly affects model outcomes.	Moderate transparency, with decision trees and linear models providing the highest interpretability.	Integrates smoothly into existing workflows when sufficient labeled data is available. Model updates require retraining, which can disrupt ongoing operations if not planned properly.	Requires periodic retraining and model evaluation. Maintenance complexity increases with dataset size and task diversity.	Privacy risks increase with sensitive datasets. Effective risk management requires secure data storage and access controls.	Scales efficiently for small to moderate datasets but struggles with large-scale deployment.	Requires relatively low user expertise and can be adopted with minimal training, provided that labeled data is available and basic algorithmic knowledge is present.
Unsupervised Learning [99]	Relatively easy to implement for clustering and anomaly detection tasks. Integration becomes challenging when unsupervised outputs require manual interpretation or downstream processing.	Requires abundant unlabeled data, with quality influencing clustering and feature extraction outcomes.	Limited explainability, as clustering results often lack clear, human-readable explanations.	Moderate operational impact, as clustering and anomaly detection can inform decision-making without altering workflows.	Minimal maintenance required, though periodic algorithm evaluation ensures consistent performance.	Lower privacy risks, though sensitive clustering features can lead to unintended exposure.	Moderate scalability, with complexity increasing for high-dimensional datasets.	Training requirements are moderate, as users need a fundamental understanding of data clustering or dimensionality reduction, but expertise in labeling is unnecessary since the method does not rely on labeled datasets.
Federated Learning [100]	Implementation complexity increases due to the need for decentralized architecture and secure communication protocols between devices.	Effective when decentralized datasets remain balanced and high quality. Heterogeneous data reduces model performance.	Transparency decreases with decentralized training and encrypted communications.	Complex integration due to decentralized training. Local model updates can disrupt workflows, particularly when devices experience connectivity issues.	Complex maintenance due to decentralized updates and device-specific troubleshooting.	Enhances privacy by keeping data local but increases risk exposure during model updates.	Scales effectively across decentralized devices, though communication overhead limits scalability.	Difficult to scale and implement due to its decentralized nature, requiring significant technical expertise and training in distributed systems, data privacy protocols, and cross-device synchronization.

Table 22 | Non-IT SME Important Factors Distributed, Transfer, Self-Supervised Learning

ML / Criteria	Ease of Implementation and Integration	Data Availability and Quality	Transparency and Explainability	Operational Impact and Workflow Integration	Support and Maintenance	Risk Management and Data Privacy	Scalability and Futureproofing	User-Friendliness and Training Requirements
Distributed Learning [101]	Integration proves challenging as distributed systems require specialized infrastructure and synchronization mechanisms across multiple nodes.	Data availability depends on distributed nodes, with quality inconsistencies complicating synchronization.	Explainability aligns with base models but decreases with complex synchronization mechanisms.	Significant operational impact due to multi-node architecture. Workflow integration depends on infrastructure readiness and efficient synchronization.	Requires continuous monitoring and synchronization across distributed nodes.	Expands attack surfaces, increasing privacy risks unless secure communication protocols are implemented.	Highly scalable, provided infrastructure supports multi-node processing.	Complex to implement due to the need for coordination across multiple nodes, requiring advanced training in parallel computing, synchronization mechanisms, and data consistency management.
Transfer Learning [102]	Easy to implement when leveraging pre-trained models, with seamless integration into existing workflows. Complexity increases when task-specific fine-tuning is required.	Requires limited data for downstream tasks but relies on high-quality pre-trained models for effective transfer.	Moderate transparency, though pre-trained models inherit explainability limitations from source tasks.	Minimal operational impact when using pre-trained models. Workflow integration remains smooth unless extensive fine-tuning is required.	Minimal maintenance when using pre-trained models. Fine-tuning increases maintenance complexity.	Privacy risks depend on the source dataset. Effective risk management requires validation of pre-trained model origins.	Scales effectively when using pre-trained models for downstream tasks.	Relatively user-friendly, as it allows SMEs to leverage pre-trained models with limited local data and minimal training, making it accessible even with modest technical expertise.
Self-Supervised Learning [103]	Implementation remains challenging due to the complexity of pre-training tasks and the need for large datasets. Integration improves when applied to downstream tasks.	Requires large, unlabeled datasets for pre-training. Data quality directly influences representation learning.	Poor explainability during pre-training. Transparency improves for downstream tasks.	High operational impact during pre-training but minimal disruption when integrating pre-trained models into downstream tasks.	High maintenance during pre-training, though downstream applications require minimal support.	Privacy risks increase when unlabeled datasets contain sensitive information.	Scales well for pre-training but requires significant computational resources.	Demands substantial domain knowledge and algorithmic understanding to configure effective pretext tasks, making it less user-friendly and requiring specialized training for successful implementation.

Table 23 | Non-IT SME Important Factors Meta, Multi-Task, Semi-Supervised Learning

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**
Meta-Learning [104]	Implementation remains complex, as meta-training requires task-specific design and integration into adaptive workflows.	Requires diverse datasets for effective meta-training. Data quality influences task-specific adaptation.	Limited transparency, as rapid task adaptation often obscures decision-making processes.	Complex workflow integration due to task-specific adaptation requirements. Operational impact remains moderate when meta-trained models are applied to specific tasks.	Demands regular model evaluation and task-specific adjustments.	Moderate privacy risks, particularly when meta-training involves sensitive datasets.	Limited scalability due to task-specific adaptation requirements.	Highly complex and requires deep expertise in algorithmic design and tuning across multiple tasks, making it impractical without extensive training and specialized support.
Multi-Task Learning [105]	Integration proves challenging when multiple tasks exhibit conflicting objectives, complicating deployment in existing systems.	Data availability remains critical for each task. Quality inconsistencies across tasks complicate shared learning.	Transparency decreases when tasks exhibit conflicting objectives.	High operational impact due to simultaneous task processing. Workflow integration becomes complex when task conflicts arise.	Requires task-specific maintenance, increasing complexity as the number of tasks grows.	Privacy risks increase when multiple tasks involve sensitive data.	Scalability decreases with task complexity and conflicts.	Demands a moderate level of expertise to properly structure shared representations and balance task interactions, requiring intermediate training for effective use.
Semi-Supervised Learning [106]	Easy to implement when labeled and unlabeled datasets share similar distributions. Integration complexity increases when data heterogeneity exists.	Requires high-quality labeled and unlabeled datasets. Poor-quality data introduces bias and reduces performance.	Moderate transparency, though unlabeled data complicates decision interpretation.	Minimal operational impact when labeled and unlabeled datasets share similar distributions. Workflow integration becomes challenging with heterogeneous data.	Moderate maintenance required to manage labeled and unlabeled datasets.	Moderate privacy risks, as unlabeled datasets may contain sensitive features.	Scales efficiently with large unlabeled datasets.	Reduces labeling effort while maintaining relatively simple implementation, making it moderately user-friendly with only basic ML training needed.

Table 24 | Non-IT SME Important Factors Privacy-Preserving, Active, Ensemble Learning

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
Privacy-Preserving Learning [107]	Implementation remains challenging due to encryption protocols and privacy-preserving mechanisms, complicating seamless system integration.	Data availability depends on decentralized environments. Encryption reduces perceived data quality.	Poor explainability due to encrypted computations and noise introduction.	Significant operational impact due to encryption protocols and privacy mechanisms. Workflow integration requires secure communication channels and infrastructure upgrades.	High maintenance demands due to encryption protocols and secure system updates.	Prioritizes data privacy through encryption and differential privacy mechanisms.	Scalability remains moderate due to encryption and differential privacy overhead.	High complexity. Strong training needed in cryptography and data protection.
Active Learning [108]	Easy to implement when integrated into existing labeling workflows. Complexity increases with iterative query strategies.	Requires partially labeled datasets. Sample quality influences query effectiveness and model accuracy.	Enhances transparency by focusing on informative samples, though query strategies remain task-dependent.	Minimal impact on workflows, as the method enhances existing labeling processes without disrupting core operations.	Requires continuous monitoring to ensure query strategies remain effective.	Privacy risks depend on query strategies and sample selection processes.	Scales effectively with sample prioritization but increases resource demands for complex query strategies.	Requires moderate training for human-in-the-loop labeling and query strategies.
Ensemble Learning [109]	Implementation complexity increases with the number of base models, complicating integration into real-time systems.	Requires multiple datasets for training base models. Quality inconsistencies propagate through ensemble predictions.	Reduced transparency due to model aggregation, though individual learners may remain interpretable.	Moderate operational impact due to increased computational demands. Workflow integration becomes complex when multiple models require continuous monitoring.	Demands regular evaluation of base models and ensemble performance.	Increases privacy risks when base models access sensitive data.	Poor scalability due to increased resource demands for multiple base models.	User-friendly; low training burden with widely available tools.

Table 25 | Non-IT SME Important Factors Generative, Few-Shot and Zero-Shot, Contrastive Learning

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
Generative Learning [110]	Challenging to implement due to complex architectures and training requirements. Integration remains feasible for data augmentation tasks.	Demands high-quality training datasets for effective data generation. Poor-quality inputs lead to unrealistic outputs.	Poor explainability, particularly for complex architectures like GANs and VAEs.	High impact during training but minimal disruption when generative models are used for data augmentation.	Requires ongoing model evaluation to maintain output quality.	Risks include generating synthetic data that resembles real, sensitive information.	Resource-intensive during training but scales effectively for data generation tasks.	Technically demanding; requires extensive training to handle data synthesis, model stability, and evaluation.
Few-Shot and Zero-Shot Learning [111]	Easy to implement for downstream tasks but complex during initial model development and deployment.	Requires limited training data, though quality remains critical for generalization.	Limited transparency, as generalization relies on abstract feature representations.	Minimal operational impact when applied to downstream tasks. Workflow integration remains smooth unless task complexity increases.	Minimal maintenance for downstream applications, though initial model updates remain complex.	Privacy risks depend on the original training datasets.	High scalability for downstream applications but limited during initial model development.	Moderately user-friendly; minimal data required but understanding of prompt design and pre-trained model usage is essential.
Contrastive Learning [112]	Difficult to implement due to complex training pipelines, though downstream integration remains straightforward.	Requires large datasets for representation learning. Quality influences positive and negative sample relationships.	Moderate explainability through enhanced feature representation.	Moderate operational impact due to complex training pipelines. Workflow integration becomes simpler for downstream applications.	Moderate maintenance required during pre-training and downstream integration.	Moderate privacy risks, particularly when positive and negative samples contain sensitive features.	Scales effectively for representation learning, though resource demands increase during pre-training.	Low user-friendliness; requires strong expertise in representation learning and careful pretext task engineering.

Table 26 | Non-IT SME Important Factors Explainable AI, Neural Architecture Search, Multi-Modal Learning

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
Explainable AI (XAI) [113]	Easy to implement for transparent models but challenging for complex architectures requiring post-hoc explanations.	Data quality directly affects model transparency and interpretability.	High transparency, prioritizing human-readable explanations of model decisions.	Minimal operational impact when integrated into existing decision-making workflows. Transparency enhances stakeholder understanding and acceptance.	Minimal maintenance required, though interpretability updates depend on model complexity.	Enhances risk management by increasing transparency.	Scalability depends on the complexity of interpretability constraints.	Moderately user-friendly, requires some training to interpret model decisions, but tools are increasingly accessible.
Neural Architecture Search (NAS) [114]	Implementation proves complex due to iterative search processes, complicating integration into production systems.	Requires high-quality datasets for effective architecture evaluation and optimization.	Poor explainability due to complex architecture search processes.	High operational impact due to iterative search processes. Workflow integration remains complex unless automated pipelines are established.	High maintenance demands due to iterative search processes and architecture updates.	Expands attack surfaces, increasing privacy risks during architecture evaluation.	Poor scalability due to iterative search processes.	Highly complex. Demands advanced expertise in optimization, search strategies, and high compute resources.
Multi-Modal Learning [115]	Challenging to implement when multiple data sources require synchronization. Integration remains easier when modalities share similar structures.	Requires balanced datasets across modalities. Quality inconsistencies reduce model performance.	Limited transparency, as feature interactions across modalities remain challenging to interpret.	Significant operational impact due to multi-source data integration. Workflow integration becomes complex when modalities exhibit imbalances or inconsistencies.	Requires continuous monitoring of data streams and modality synchronization.	Privacy risks increase with multi-source data integration.	Scalability decreases with increasing modality complexity.	Technically challenging. Necessitates expertise in integrating diverse data types and managing complex model interactions.

F) Initial Survey Structure

Table 27 | Structure of Survey on Identifying Processes in Logistics SMEs Suitable for ML Adoption

Segment	Question	Possible Answers
Demographic and Organizational Background	What is your role in the organization?	○ Owner / CEO ○ Manager ○ Operations Staff ○ Other (please specify):
	How many employees does your organization have?	○ Fewer than 10 ○ 10-50 ○ 51-100 ○ 101-150 ○ 151-200 ○ 201-250
	What type of logistics services does your company provide?	○ Warehousing ○ Inventory Management ○ Transportation and Delivery ○ Supply Chain Management ○ Reverse Logistics ○ Other (please specify):
	How would you describe the primary focus of your company?	○ Domestic Logistics ○ International Logistics ○ Both
Current Operational Processes	What are the key daily processes in your organization?	○ Inventory Management ○ Route Allocation ○ Purchase Planning ○ Scheduling ○ Supply Chain Tracking ○ Other (please specify)
	What challenges or inefficiencies do you commonly experience in your operations?	○ Delays ○ High Costs ○ Inaccurate Planning ○ Other (please specify)
Process-Specific Challenges and Objectives	Are there any processes that require significant manual effort or are prone to errors?	○ Yes, please describe: ○ No
	Are there processes where decision-making takes significant time or is prone to delays?	○ Yes, please describe: ○ No
	Are there processes in your company that involve handling large volumes of data	○ Yes, please describe: ○ No
	Would automating certain repetitive tasks improve productivity in your organization?	○ Yes, please specify which tasks: ○ No
	Are there areas in your company where forecasting or planning improvements could reduce costs or enhance efficiency?	○ Yes, please describe: ○ No
Awareness and Willingness to Adopt Technological Solutions	Has your organization previously adopted any digital or technological tools to improve operations?	○ Yes, please specify which tools: ○ No
	What are your main concerns regarding the adoption of new technologies in your company? (Multiple Selection)	○ Cost ○ Complexity of Implementation ○ Training and Skill Requirements ○ Potential Data Privacy Issues ○ Lack of Trust in New Technologies ○ Unclear Steps to Take Towards AI/ML ○ Other, please specify:
	How do you envision technology improving your current operations?	○ Faster decision-making ○ Better forecasting ○ Reduced Costs ○ Other, please specify:
Final Open-Ended Questions	In your opinion, what areas of your company would benefit the most from new tools or processes?	
	Do you have any additional comments or suggestions about your company's operations and challenges?	

G) Prioritized Requirements

Business Requirements

Table 28 | 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 29 | 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 30 | 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 31 | 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

H) 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 ML, 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?

ML 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 ML 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, ML 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 Collab, 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 and 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?

ML 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 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 (e.g., 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 and 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, prioritize 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, 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 ML 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 ML, 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 similar 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 (even if 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 (e.g., 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?

ML 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 (e.g., 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?

ML 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-experienced 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.

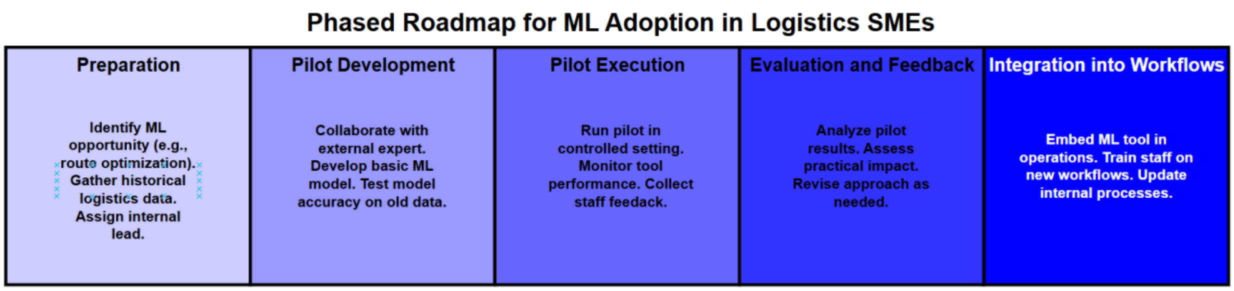

Figure 5 | Change Management Phased Roadmap Guidelines

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 (e.g., 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 (e.g., 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 ML, 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 (e.g., 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 behavior, 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 (e.g., 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 ML 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 so that staff can quickly recognize 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. When employees report a recurring inefficiency, the process owner or designated lead should initiate a short, structured reflection with those involved. This could follow a format: (1) What was expected? (2) What occurred? (3) Why did it diverge? (4) What should be adapted?

The 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 ML 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 (e.g., 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 (e.g., delivery performance, order cycle times, fuel usage, or vehicle utilization) and to 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 ML 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 ML 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 ML 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 (e.g., 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 ML 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 (e.g., 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, for instance, 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 ML 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?

ML 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 (e.g., 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 such as 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 ML 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 prioritized if it strengthens compliance, branding, or partnership potential.

Where internal technical capacity is limited, SMEs may reach out to sector-specific innovation centers 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 ML 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 ML 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 (e.g., 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 focusing on 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 centers, 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 ML 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 favor 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 (e.g., 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 ML 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 RBAC mechanisms to ensure that employees only access the data and systems required for their functions. Additionally, 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 ML 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 simple table listing systems, users, access rights, and 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 (e.g., *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 prioritize 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 ML 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 (e.g., 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 ML 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?

ML 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 ML 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?

ML models depend not only on internal process data but also on external context to achieve robustness and accuracy. In logistics, real-world variables (e.g., traffic delays, seasonal fluctuations, 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, for instance, 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 ML 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 (e.g., working prototype, performance evaluation, workflow integration suggestions) and what constraints (e.g., 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 ML 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 to 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 ML 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 favored 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 ML 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 ML 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 in a practical, transparent, and integrated into day-to-day operations way 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 ML 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 and 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.

I) Case Studies

I1) Spare Parts Management Optimization at Company A

Introduction of Problem and Process Selection

The spare parts management process at Company A has been selected to serve as a case study of the proposed MLPRALS framework. The selection is based on its operational significance, the presence of structural inefficiencies, survey feedback, and insights gained through process analysis. As a logistics-focused SME, Company A relies heavily on the effective management of spare parts to support its field operations. However, several weaknesses in the current process inhibit its ability to achieve efficient, scalable, and data-driven inventory planning. The existing spare parts management process, illustrated in Figure 6, is characterized by a fragmented approach to data utilization and limited predictive capability. Although operational transactions, such as engineer part usage and return registrations, are logged within the ERP system, inventory planning activities continue to be largely manual and intuition based. Planning decisions are typically supported by spreadsheet analysis and subjective experience, without systematic exploitation of the historical usage data or real-time operational insights available within existing systems. Consequently, demand forecasts for spare parts are reactive, based on immediate observations rather than predictive modeling.

Further inefficiencies arise from the handling of part returns and stock replenishment. Refurbishment decisions are made manually after the physical inspection of returned items, delaying the reintegration of refurbished parts into available stock. The absence of live tracking for part returns and refurbishments introduces uncertainty into inventory visibility, complicating procurement planning and leading to stock shortages that are often detected only after engineers attempt to pick unavailable items. The lack of dynamic forecasting and integration between stock movements, refurbishment workflows, and supplier management prevents proactive mitigation of stock risks, particularly given the long lead times associated with external suppliers. These challenges expose Company A to recurring operational risks, including elevated downtime in field services, increased emergency procurement costs, and inefficiencies in supplier engagement. Addressing these limitations through the structured application of the MLPRALS framework offers the potential to transition the spare parts management process from a reactive model to a predictive and adaptive system, underpinned by better data integration and structured decision support.

To address the identified inefficiencies in Company A's spare parts management process, an optimized approach incorporating ML has been developed. Based on the comparative analysis of ML methods conducted in this study, online learning is selected as the most suitable solution. The optimized process, depicted in Figure 7, introduces an online learning model that dynamically adjusts stock replenishment decisions based on real-time operational data, replacing the previous reliance on static thresholds and manual interventions.

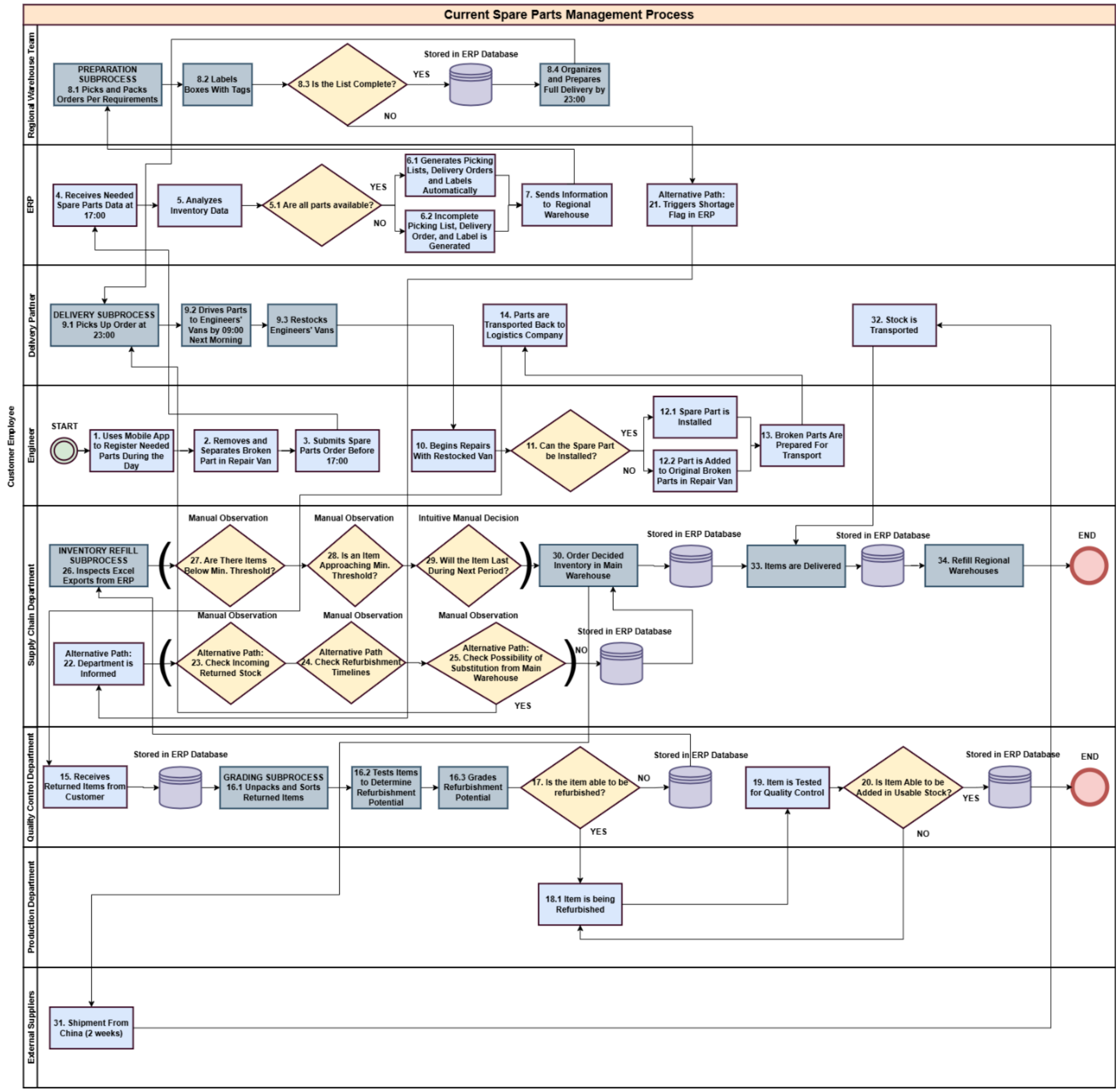

Figure 6 | Current Spare Parts Management Process at Company A

This transformation enables predictive inventory management by integrating daily consumption reports, refurbishment updates, and warehouse stock records, thereby reducing stockouts and enhancing coordination between warehouse operations and reverse logistics. The MLPRALS framework is applied to guide Company A's transition from its current practices to the optimized state, ensuring that improvements in data readiness, system integration, and organizational alignment are systematically addressed. Through this structured advancement, Company A strengthens its capacity to achieve sustainable, intelligent spare parts management.

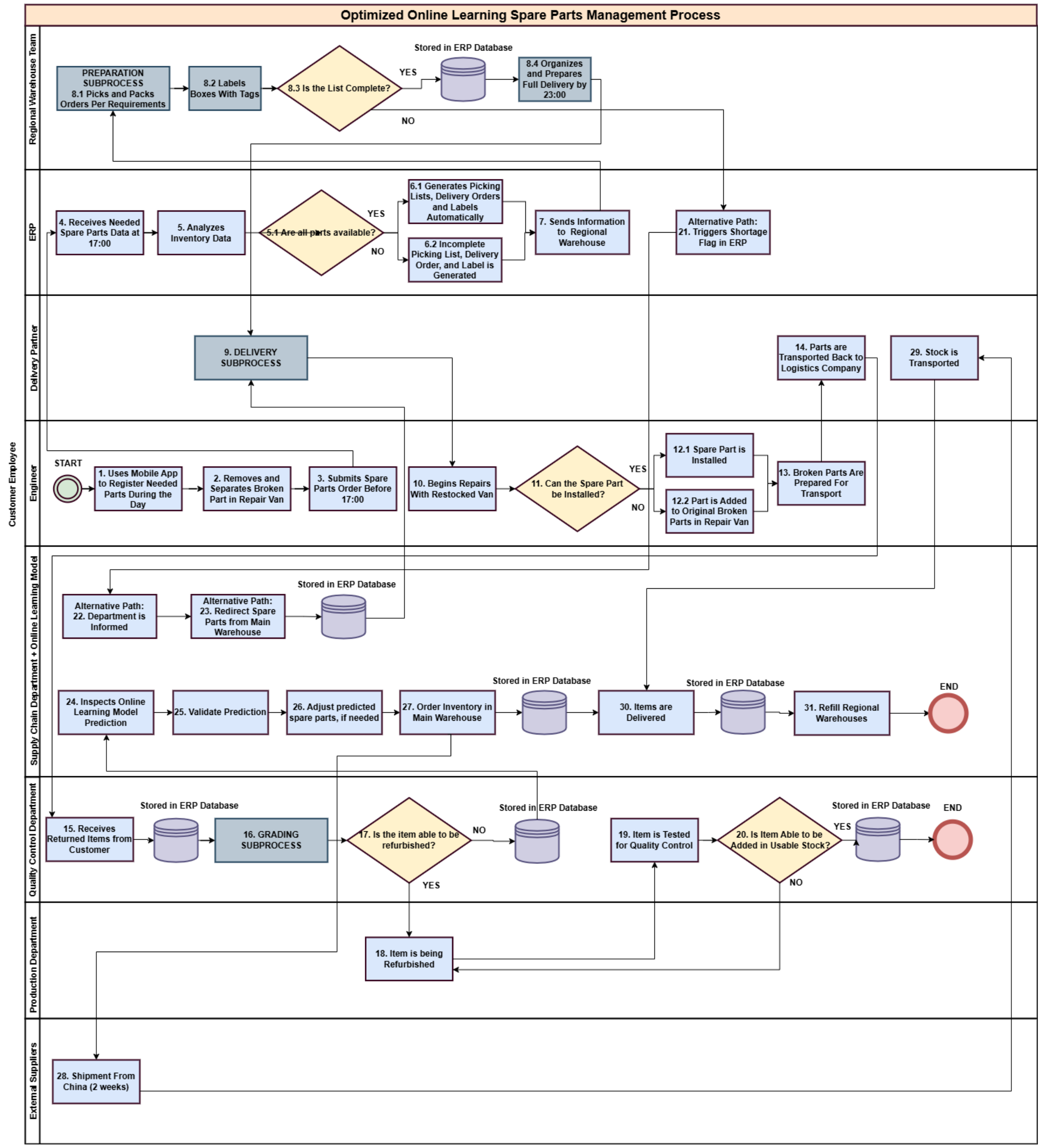

Figure 7 | Optimized Spare Parts Management Process at Company A

Readiness Score MLPRALS Framework

The category-level readiness score of Company A is presented in Figure 8, with detailed results provided in Table 32. According to the MLPRALS framework, Company A demonstrates the highest level of readiness among the three participating case studies. Nevertheless, while it shows significant progress, it does not yet fully meet the established thresholds for ML readiness. To be considered ML-ready, an organization must achieve at least level 3 across all assessed categories, with a minimum of level 4 specifically required in data readiness. Although Company A approaches these thresholds more closely than its peers, further improvements remain necessary to ensure complete readiness for the integration of ML into its spare parts management process.

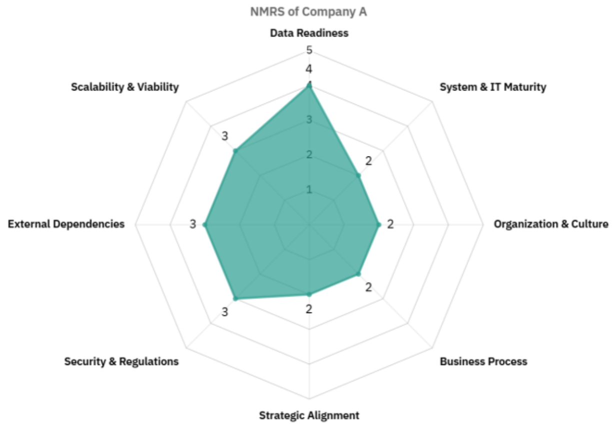

Figure 8 | Readiness Score Company A

Targeted Guidance MLPRALS Framework

Following the analysis of the readiness score of Company A, tailored guidance is provided to support the application of the MLPRALS framework to Company A's spare parts management process and their overall ML readiness, while bridging the gap between the current and desired state of the process.

Data Readiness

Company A is assessed as meeting the minimum threshold for ML readiness in the data readiness category, according to the MLPRALS framework. This positioning reflects structured efforts already undertaken to improve data collection, organization, and availability within the spare parts management process. However, to ensure long-term performance and to fully support the introduction of an online learning-based replenishment model, further improvements are recommended.

To enhance current capabilities, an optimized data architecture is advised, as depicted in Figure 9. This architecture is built around a relational structure that integrates key operational domains, including live consumption data, refurbishment activity, historical inventory snapshots, purchase orders, and forecast inputs. By consolidating these datasets under a unified and normalized data model, operational transparency is increased, data redundancy is reduced, and the system is equipped to provide accurate, context-aware inputs to the ML model.

The proposed structure also ensures real-time compatibility with ERP systems and supports automatic ingestion of field updates and refurbishment outcomes. As such, it enables continuous model learning without manual data transfers, reducing lag between operational events and predictive adjustments. This configuration significantly strengthens the predictive engine's ability to generate timely and precise replenishment suggestions while also supporting future scalability. Additionally, structured referential integrity across tables reinforces data quality and traceability, which are critical for sustaining model accuracy over time.

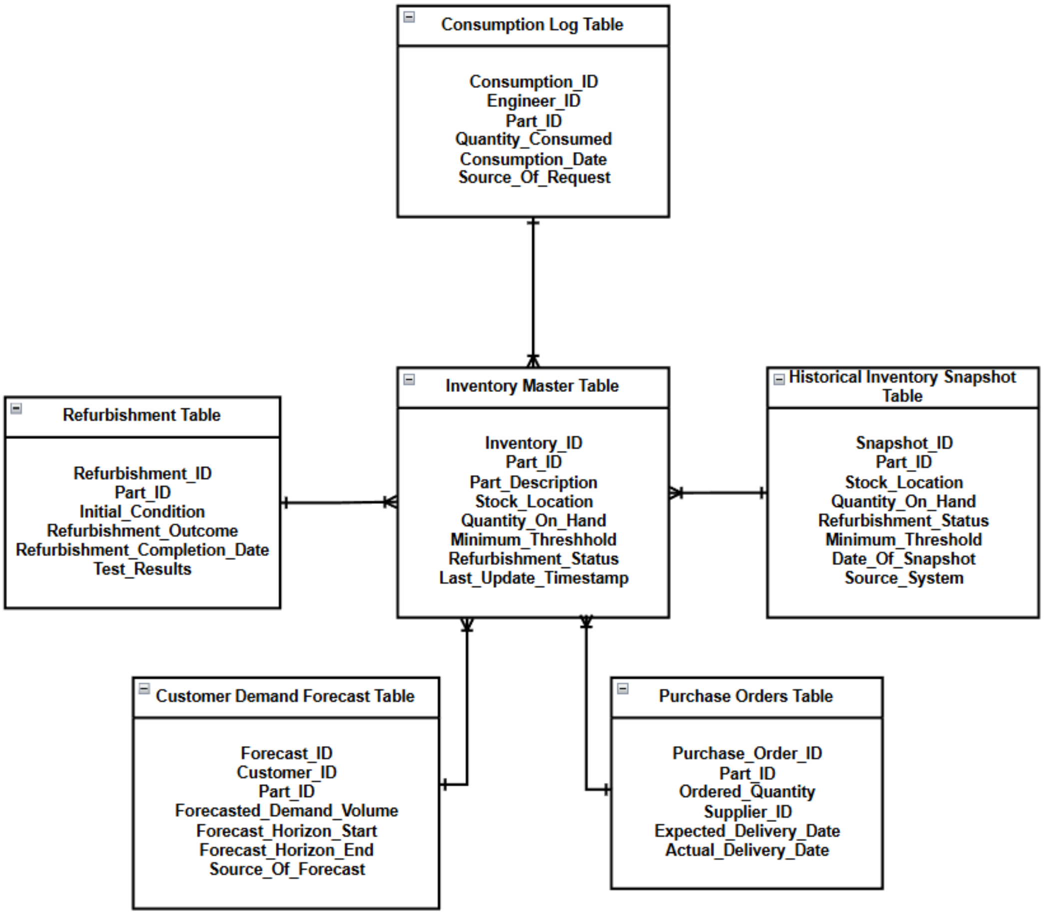

Figure 9 | Proposed Optimized Data Structure Company A

System & IT Maturity

To ensure system and IT maturity within the spare parts management process, Company A must strengthen the compatibility between its core operational systems and the ML components introduced in the optimized architecture. Although existing ERP systems already provide foundational functionality for inventory and procurement management, integration gaps persist that limit the seamless interaction of these tools with ML-driven components. These limitations include insufficient access to structured exports, inconsistent data schemas across modules, and minimal automation of information exchange. Addressing these shortcomings is critical to enabling ML integration and to realizing the full potential of predictive replenishment within the spare parts domain.

To address this, a revised data flow model has been developed, presented in Figure 10. This architecture integrates core operational entities such as the ERP, regional and central inventory databases, refurbishment and grading subsystems, and the financial platform, establishing streamlined communication channels through secure API protocols. Key improvements include the establishment of real-time links between consumption logs, mobile applications for field engineers, and the central inventory database, allowing the ML model to receive continuous updates on usable stock, refurbishment outcomes, and customer demand signals. Additionally, predicted demand from the online learning model flows directly into the ERP module, which then facilitates automated procurement actions and inventory restocking decisions.

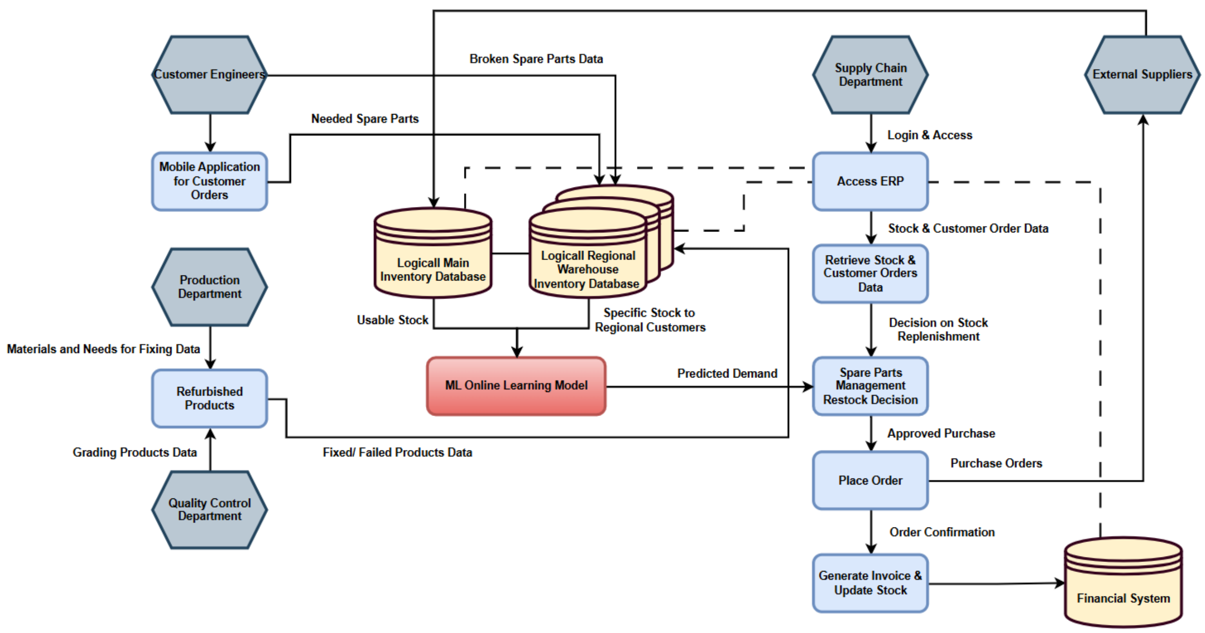

Figure 10 | Proposed Data Flow Diagram for Company A

The advised system configuration ensures several operational improvements. First, it enhances data interoperability across subsystems, thereby reducing manual exports and reformatting requirements. Second, it improves the quality and frequency of input available to the ML model, which relies on synchronized consumption, refurbishment, and stock data to generate accurate forecasts. Third, it allows ML outputs to be operationalized immediately, feeding predicted stock requirements directly into procurement routines. This reduces response time and lowers the likelihood of understocking or overordering. Finally, improved system connections also support auditability and traceability, as all ML-related decisions and predictions are logged against structured identifiers within the ERP and associated data tables. This level of integration is essential not only for deploying the ML model but also for scaling its use and for embedding it into daily decision-making. By enabling clean, structured data extraction and two-way communication between systems, Company A can reduce overhead costs, accelerate ML experimentation cycles, and maintain control over the end-to-end spare parts planning process. Such an approach ensures the long-term sustainability of the technology and safeguards against software lock-in, while allowing flexible adaptation as operational needs evolve.

Organizational & Cultural Readiness

To advance organizational and cultural readiness within Company A, it should strengthen digital skills across relevant departments and cultivate a participatory environment in which employees actively engage with ML-driven process innovation. While Company A demonstrates relatively strong maturity in this category, further enhancement of digital fluency and internal collaboration is needed to support the sustained use of ML in spare parts forecasting and inventory decision-making.

Given the complexity of the current spare parts management workflow, digital literacy plays a critical role in enabling employees to interpret ML-generated demand forecasts and apply them within ERP-supported procurement tasks. Personnel involved in inventory control, refurbishment planning, and replenishment ordering must be capable of interacting with structured data inputs and interpreting insights embedded in dashboards or automated reports. Targeted training should therefore be introduced for planners, warehouse leads, and supply chain staff to improve their ability to navigate ERP modules, validate forecast accuracy, and integrate system-generated recommendations into operational decisions. For example, training on how to cross-reference predicted part shortages with refurbishment lead times would improve responsiveness and reduce manual overcorrection.

In parallel, Company A should establish structured channels for capturing employee insights regarding spare parts availability, restock anomalies, or overlooked inefficiencies. Those responsible for grading refurbished items or preparing restock orders possess critical domain knowledge about part demand volatility and lead time variability. These insights are essential for validating and refining ML models over time. Monthly suggestion forms, quick feedback discussions during shift meetings, or digital collection tools embedded within the ERP system could serve this purpose effectively. Employees who raise process improvement ideas should be invited to participate in pilot testing of ML features, such as forecast validation steps or procurement adjustment recommendations.

To support long-term adoption, visible recognition of employee contributions should be institutionalized. Acknowledging staff involvement in ML process development reinforces organizational buy-in and builds trust in system outputs. This becomes particularly relevant when ML predictions are used to influence critical tasks such as parts allocation, stock redistribution, or purchase order initiation. By aligning digital skill development and participatory practices with the specific structure and demands of the spare parts management process, Company A can ensure that its workforce remains equipped and engaged as ML becomes more deeply embedded in operational routines.

Business Process Readiness

To strengthen business process readiness within Company A's spare parts management process, targeted improvements are advised. Although the company exhibits a degree of systematization, several critical aspects require enhancement to ensure a scalable and ML-compatible operational environment.

First, it is essential that Company A formalizes the planning of spare parts, which currently remains largely dependent on individual decision-making by planners. Although a central warehouse governs initial purchasing decisions before distributing spare parts to regional depots, the lack of uniform, documented procedures introduces variability that compromises data consistency and process reliability. Therefore, a clear and accessible standard operating procedure must be developed. This documentation should describe each step involved in forecasting, purchasing, and reallocating spare parts, including how extracted data from ERP systems and spreadsheets are to be interpreted. The process must reflect actual operational practices rather than idealized workflows and should be disseminated among all relevant staff. Practical tools such as editable checklists, annotated flow diagrams, or illustrated work instructions can be used to maintain accuracy and ease of updates. Supervisors should be tasked with ensuring adherence and with making revisions where operational realities evolve.

In parallel, Company A must strengthen its use of data-driven decision-making within the spare parts planning function. Although ERP platforms and inventory monitoring tools are available, planners continue to rely heavily on static Excel spreadsheets extracted from operational systems. This introduces latency and reduces responsiveness. To address this, it is advised that dynamic dashboards be implemented, capable of real-time or near-real-time visualization of key inventory indicators. These dashboards should prioritize focused metrics directly linked to spare parts performance, such as inventory turnover rate, forecasted shortages, lead time variability, and stock reallocation frequency. Particular attention must be given to making dashboards accessible and actionable for planners, with clear thresholds and alerts that assist in prioritizing procurement and redistribution activities.

Integration of these dashboards into daily routines is equally critical. Planning sessions should begin with a review of updated dashboards, allowing decisions to be grounded in current, structured data rather than subjective judgment. A designated point of contact should oversee dashboard maintenance to ensure continuous data reliability. Furthermore, outcomes influenced by dashboard insights should be documented, allowing Company A to build a repository of use cases demonstrating operational improvements achieved through data-driven methods.

Strategic Alignment

To ensure strategic alignment in the transition toward ML-supported spare parts management, Company A must establish a clearly delineated and scalable financial planning structure. Although initiatives toward digital improvement have been informally pursued, no formalized budgeting has yet been assigned specifically to ML-driven optimization. As the spare parts management process has already been recognized internally as a critical area for improvement and considering that the identified weaknesses align with the operational benefits offered by online learning models, the establishment of a pragmatic financial framework becomes imperative.

Financial planning must begin by preparing a cost outline dedicated to the piloting and gradual deployment of the ML-enhanced process. The expected expenses should include initial data preparation, cloud storage or computational resources for model training, licensing fees for necessary software, and external advisory support if needed. Given that Company A already engages in small-scale improvement initiatives and maintains external innovation partnerships, accessing public subsidies, digitalization vouchers, or co-funded research collaborations may significantly reduce the internal financial burden.

Moreover, realistic ROI expectations must be defined prior to the pilot phase. In this context, the primary anticipated benefits would involve the replacement of intuition-based decision-making with data-driven approaches, thereby improving inventory turnover, reducing the frequency of spare parts shortages, and optimizing warehouse replenishment cycles. Rather than projecting abstract financial gains, Company A should translate these expectations into tangible operational metrics, such as a percentage reduction in stockouts, shorter average replenishment lead times, or higher spare part utilization rates.

To sustain discipline throughout the deployment, costs and benefits must be continuously monitored. Company A, having internal financial tracking capabilities, should integrate ML project accounting into its existing structures, performing quarterly reviews to assess the actual versus projected performance. Even if the initial results do not fully achieve the expected targets, documenting the financial and operational impacts systematically will support iterative refinement and scaling decisions based on empirical evidence.

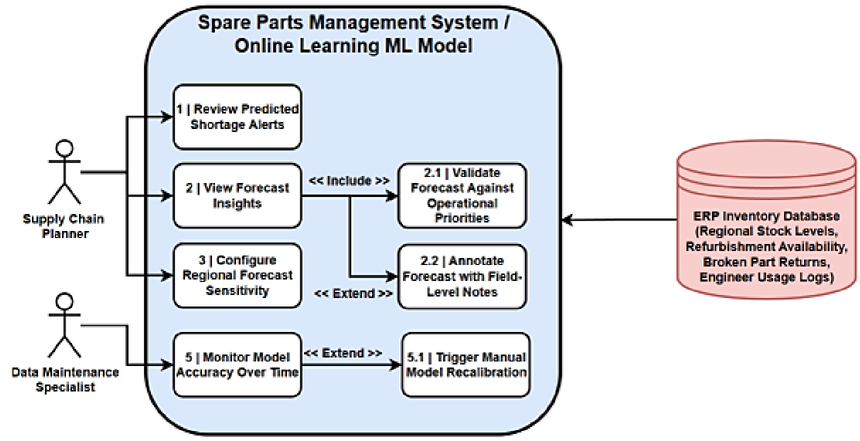

Figure 11 | Use Case Diagram of the Optimized Spare Parts Management Process

The use case diagram presented in Figure 11 illustrates the primary interactions between key users and the ML-supported spare parts management system. Specifically tailored to Company A's operational context, the diagram highlights how forecasted shortage alerts, demand insights, and sensitivity configurations are integrated into the daily responsibilities of the supply chain planner and the data maintenance specialist. This visual representation clarifies how the online learning model facilitates informed decision-making by enabling users to review, validate, and annotate forecast outputs based on real-time ERP inventory data, refurbishment status, and engineer usage logs. Furthermore, the diagram outlines additional functionalities, such as model monitoring and recalibration, that ensure forecast accuracy is maintained over time. By delineating these interactions, the use case diagram reinforces the practical applicability of the proposed ML solution and demonstrates how it supports operational agility, predictive planning, and long-term scalability within Company A's spare parts management process.

Security & Regulatory Compliance

According to the MLPRALS framework, Company A is considered prepared in the area of security and regulatory compliance, having implemented key baseline measures such as MFA and RBAC for its internal systems. These controls support secure user authentication and access limitation within the organization. Nonetheless, given the operational involvement of external business partners who interact with the spare parts ordering system, further reinforcement of security architecture is advised to ensure comprehensive protection across all digital interfaces. To this end, the security architecture presented in Figure 12 is proposed as an enhancement to the current setup. This architecture introduces a layered security model integrating both internal and external access pathways. Internally, it builds upon existing MFA and RBAC mechanisms by formalizing secure authentication workflows through a centralized Google Cloud Console. Externally, it incorporates OAuth2-based token authentication and ECDSA digital signatures for customer business users who signal spare parts demand. These additions provide authenticated and verifiable access without exposing critical system functions to unauthorized entities.

Furthermore, the architecture implements TLS-based encryption (AES-256) for all data exchanges between the ERP system, external databases, and the ML model. This ensures that sensitive operational data, such as stock levels and engineer usage logs, remains confidential and tamper-proof. An audit logging mechanism is included to track and record system interactions, which supports regulatory compliance, accountability, and traceability in cases of breach or misuse. Additional components such as anomaly detection and input validation further secure the interface between the ML model and the operational databases. These features prevent the injection of faulty or manipulated data that could compromise prediction quality or disrupt replenishment decisions. Taken together, this proposed architecture not only secures Company A's current digital infrastructure but also enables scalable and responsible integration of ML capabilities into its spare parts management process.

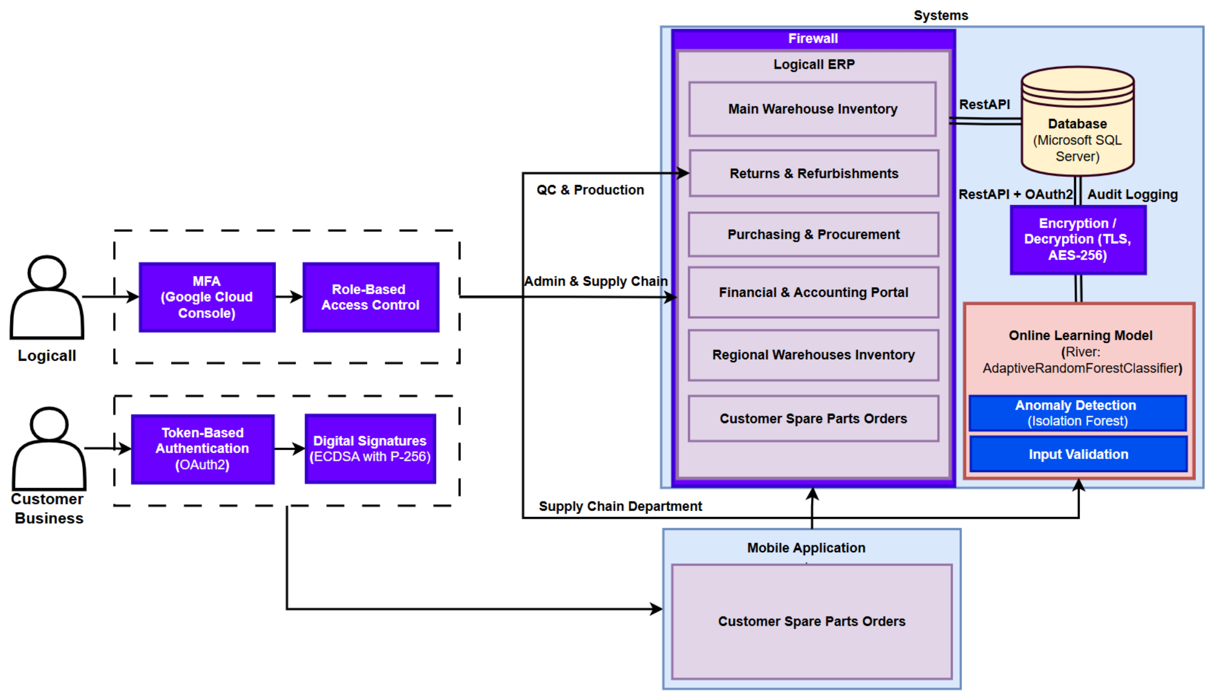

Figure 12 | Proposed Security Architecture for Spare Parts Management Process

I2) Purchase Planning Optimization at Company B

Introduction of Problem, Process Selection, and Desired Optimization

To illustrate a case study of the application of the proposed MLPRALS framework, the purchase planning process of Company B is selected based on its suitability, demonstrated need, survey results, and insights gathered through an interview with the company's representative. The current purchase planning process, depicted in Figure 13, at Company B, a logistics-focused SME, faces several structural and operational challenges that limit its efficiency and scalability. The process is predominantly manual and relies heavily on human intuition for stock assessment and procurement decisions. Planners review inventory levels in their ERP system and evaluate supplier prices without systematic use of historical sales data or predictive analytics. Although historical records are available, they are underutilized, resulting in a reactive rather than strategic purchasing approach. This reliance on subjective judgment increases the risk of overstocking and financial losses from forced resale of excess inventory at discounted prices. Overstocking represents a significant challenge due to the nature of the product, as its quality deteriorates over time until it becomes unsellable.

Additionally, the planning process and the manual inspection of previous sales does not distinguish between products sold at full value and those liquidated through auctions, leading to misinterpretations of product demand. Seasonal purchase planning is also manually performed, with estimations based on past experience rather than data-driven forecasting. These inefficiencies are further compounded by a lack of structured data-driven decision-making and limited integration of market trend analysis. Consequently, the current approach inhibits proactive inventory management and exposes the company to significant financial and operational risks. Addressing these challenges through the application of the MLPRALS framework offers a pathway to optimizing purchase planning, enhancing decision quality, and reducing reliance on intuition.

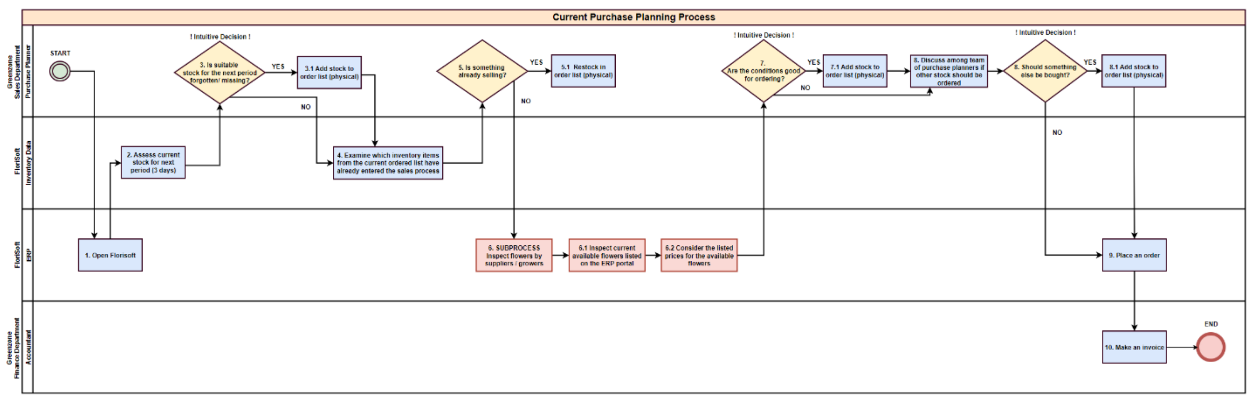

Figure 13 | Current Purchase Planning Process at Company B

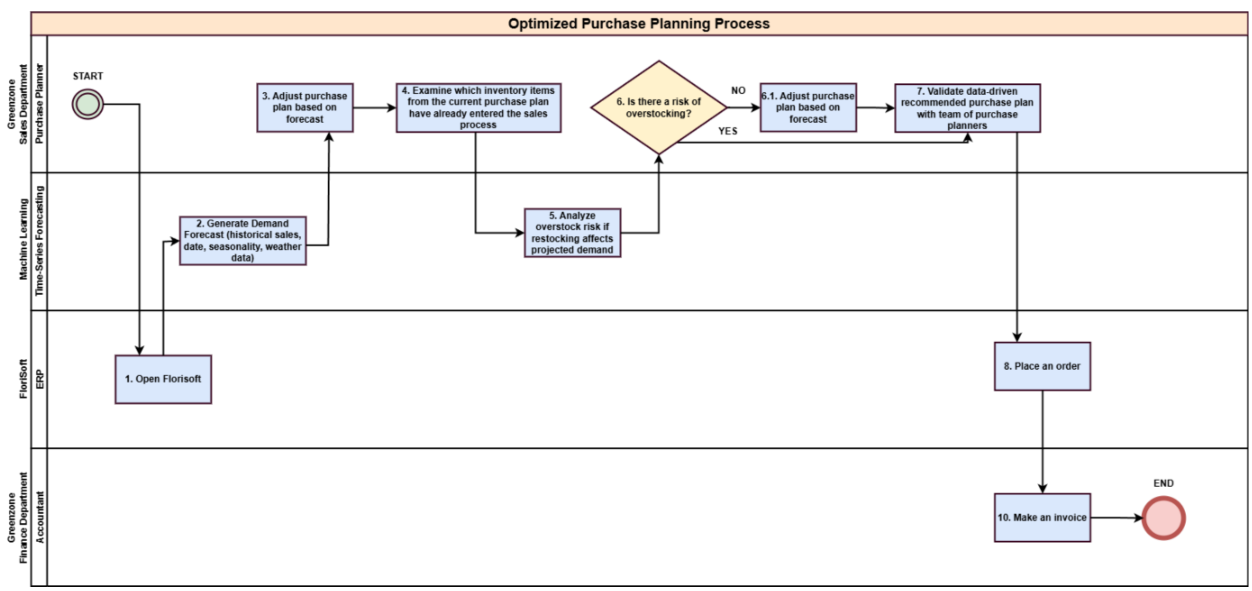

Figure 14 | Optimized Purchase Planning Process at Company B

To address the shortcomings identified in the current process, a ML-optimized purchase planning process has been developed. Based on the operational requirements of the process and the comparative analysis of various ML techniques, models, and paradigms conducted in this study, time-series forecasting is identified as the most suitable approach. A time-series forecasting model is incorporated into the optimized purchase planning process, as depicted in Figure 14. This model replaces the reliance on intuition-based decision-making and introduces data-driven predictions for future demand, thereby enabling more accurate and timely purchasing decisions. The new process enhances the current one by systematically utilizing historical sales data, distinguishing between regular and auction-based sales, and accounting for seasonal trends. As a result, it mitigates the risks of overstocking and understocking, improves inventory turnover, and reduces financial losses from unsold products.

In order for Company A to transition from its current purchase planning practices to the proposed optimized process and to maximize the benefits of ML integration, its readiness levels are assessed using the MLPRALS framework. Based on this analysis, targeted guidance is provided to support the company's progression toward successful ML adoption.

Readiness Score MLPRALS Framework

The category-level readiness score of Company B is presented in Figure 15, with detailed results provided in Table 32. According to the MLPRALS framework, Company B does not meet the required thresholds for ML readiness in any of the assessed categories. To be considered ML-ready, an organization must achieve at least level 3 across all categories, including a minimum of level 4 in data readiness. Company B's current scores fall short of these criteria.

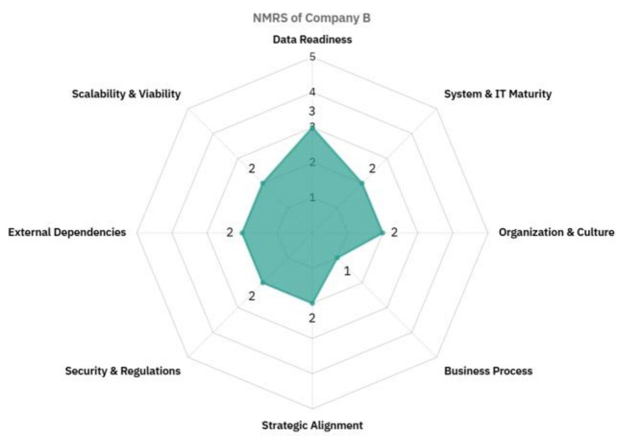

Figure 15 | Readiness Score Company B

Targeted Guidance MLPRALS Framework

Following the analysis of the readiness score of Company B, tailored guidance is provided to support the application of the MLPRALS framework to Company B's purchase planning process and their overall ML readiness, while bridging the gap between the current and desired state of the process.

Data Readiness

To be considered ready in the data readiness category, Company B must substantially strengthen its data management capabilities, building an interconnected foundation that supports the future integration of ML into its purchase planning process. Achieving this requires simultaneous improvements across data collection, quality assurance, system integration, and historical data structuring, each reinforcing the others to create a cohesive data environment.

The transition must begin by progressively automating data collection. Manual data entry, which remains prevalent across purchase planning and inventory management activities, introduces errors and delays that compromise both operational efficiency and ML suitability. Company B should introduce system-driven mechanisms, such as barcode scanning linked to warehouse systems, mobile applications for status updates, and structured workflow triggers that automatically record events. Where automation is not yet possible, operational mapping must be performed to prioritize high-frequency and high-risk manual inputs for replacement. The goal is to shift from reactive data recording to real-time, system-based capture, ensuring that data reflects actual operational events with minimal human intervention.

However, automation alone is insufficient if the data captured lacks consistency and reliability. Company B must simultaneously embed validation mechanisms that ensure the structural and statistical quality of its datasets. Key fields, such as order dates, stock quantities, and delivery durations, must be governed by predefined rules, and anomalies must be detected early through lightweight validation routines. Weekly or monthly reviews of data completeness and accuracy should become standard practice, supported by simple logging of corrections and observed issues. By institutionalizing basic quality checks, Company B will prevent error accumulation and create a stronger foundation for reliable ML model training.

To unlock the full potential of its operational data, integration between systems must also be addressed. Currently fragmented datasets must be logically connected, with harmonized identifiers and shared reference structures across inventory, supplier, and order management tools. Even if full automation is not yet feasible, structured exports and field-aligned manual processes should be implemented to create unified datasets. This integrated environment ensures that ML models can draw from comprehensive information streams rather than isolated, incomplete sources, enabling more accurate forecasting and decision support.

Historical data consolidation completes the readiness foundation. Company B must retrieve and structure past records, including purchase histories, stock movement logs, and supplier transactions, into standardized, analyzable formats. Consistency in column names, data types, and units of measurement must be ensured, while known gaps and anomalies must be documented. Centralized storage solutions, such as cloud repositories or internal databases linked to the ERP system, should be used to make datasets readily accessible for future ML initiatives. Even partial consolidation can significantly reduce future effort, accelerate model development, and improve the reliability of ML-driven insights.

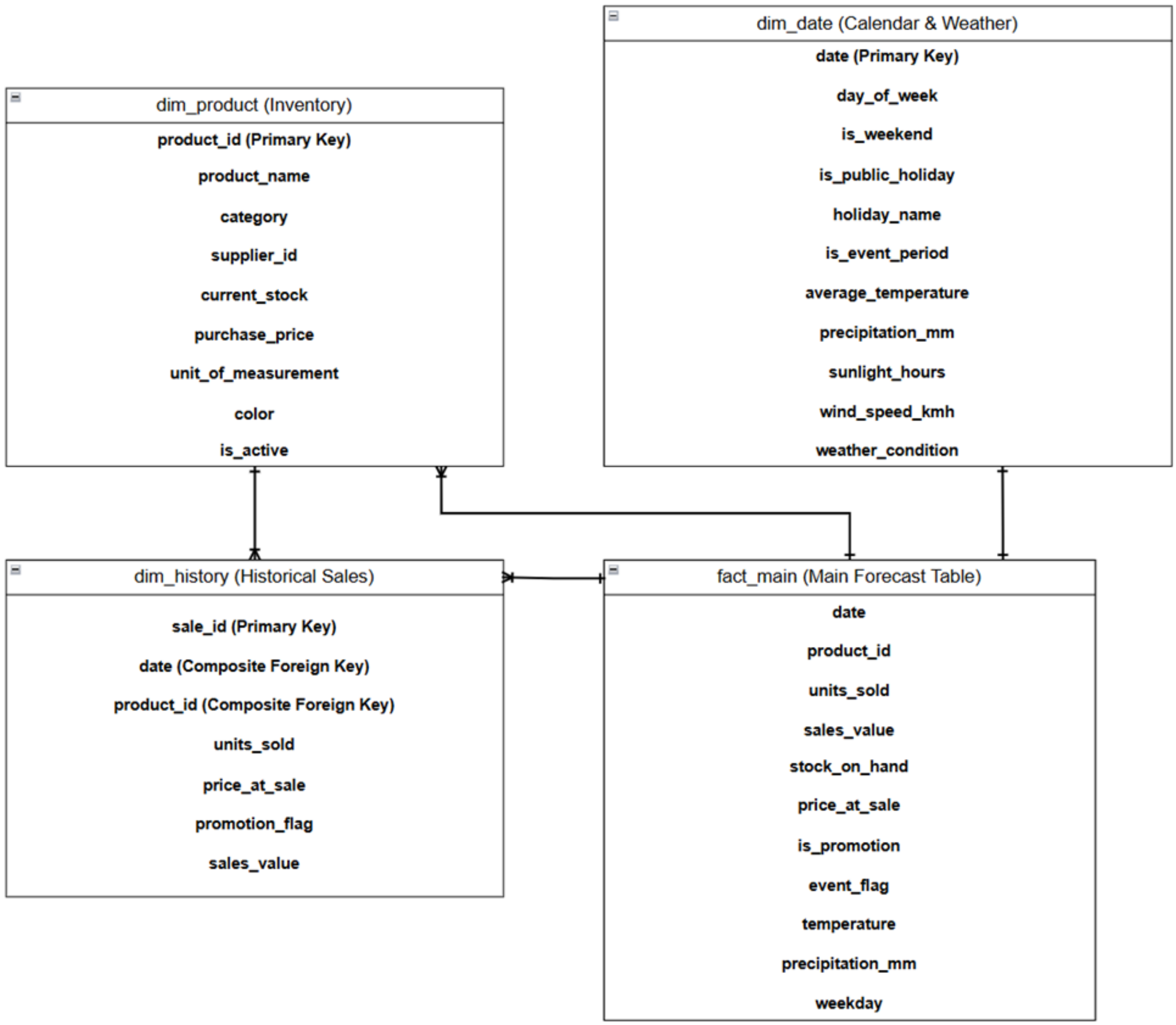

Figure 16 | Proposed Optimized Data Structure Company B

To further support the data readiness of Company B, an optimized data structure, depicted in Figure 16, is advised to facilitate the integration of a time-series forecasting model. Compared to the current situation, where data is fragmented across disconnected systems, inconsistently formatted, and partially recorded through manual entry, the proposed structure introduces a unified schema that centralizes key inputs such as historical sales, inventory levels, and contextual calendar data. This configuration enhances traceability, supports automated updates, and ensures that all relevant variables are aligned across tables through shared identifiers. The improved structure reduces data preparation effort, enables consistent forecasting inputs, and creates a scalable foundation for reliable ML deployment within the purchase planning process.

System & IT Maturity

To strengthen readiness in the System and IT Maturity category, Company B must develop both the computational capacity and the digital stability required to support ML-driven purchase planning. This involves establishing sufficient resources for model development and testing, while ensuring that IT systems remain secure, updated, and operational. Given the computational demands of time-series forecasting, Company B should assess whether its current infrastructure can support data preparation, model training, and inference without disrupting core activities. In the likely case of limitations, cloud platforms such as Google Collab or AWS SageMaker offer low-cost, scalable alternatives suited to SMEs. These platforms allow for experimentation without investment in high-spec local hardware and can be integrated gradually based on needs and available support.

Internally, computing assets should be documented, including specifications such as RAM and processing power. ML-related tasks should be scheduled to avoid system overload, and basic protocols for file organisation, backups, and tracking of model outputs should be introduced. These steps improve reproducibility and prevent system bottlenecks.

In parallel, a structured IT maintenance plan must be implemented. Company B should formally assign IT support responsibilities to internal staff or an external provider and introduce regular maintenance routines. These must include system and software updates, hardware health checks, antivirus monitoring, and recovery testing. Scheduled reminders or service agreements can support consistency. Additionally, a simple issue log should be maintained to track system failures and recurring problems. Escalation procedures must be defined to ensure fast response in the event of system disruption.

To complement the improvements proposed under System and IT Maturity, an optimized data flow, presented in Figure 17, is recommended for Company B's purchase planning process. The advised data flow diagram reflects a more interconnected structure, in which internal systems such as the ERP, inventory database, and financial system are integrated with external and auxiliary data sources, including historical sales and weather-related information. The model ensures that all critical data flows into the ML forecasting model through clearly defined interfaces, enabling consistent and traceable data exchange across platforms. By establishing this streamlined flow, Company B reduces redundancy, enhances system interoperability, and minimizes manual intervention during decision-making. It further facilitates automation of the stock update and invoice generation process, reinforcing end-to-end digital continuity and preparing the process for reliable, scalable ML integration.

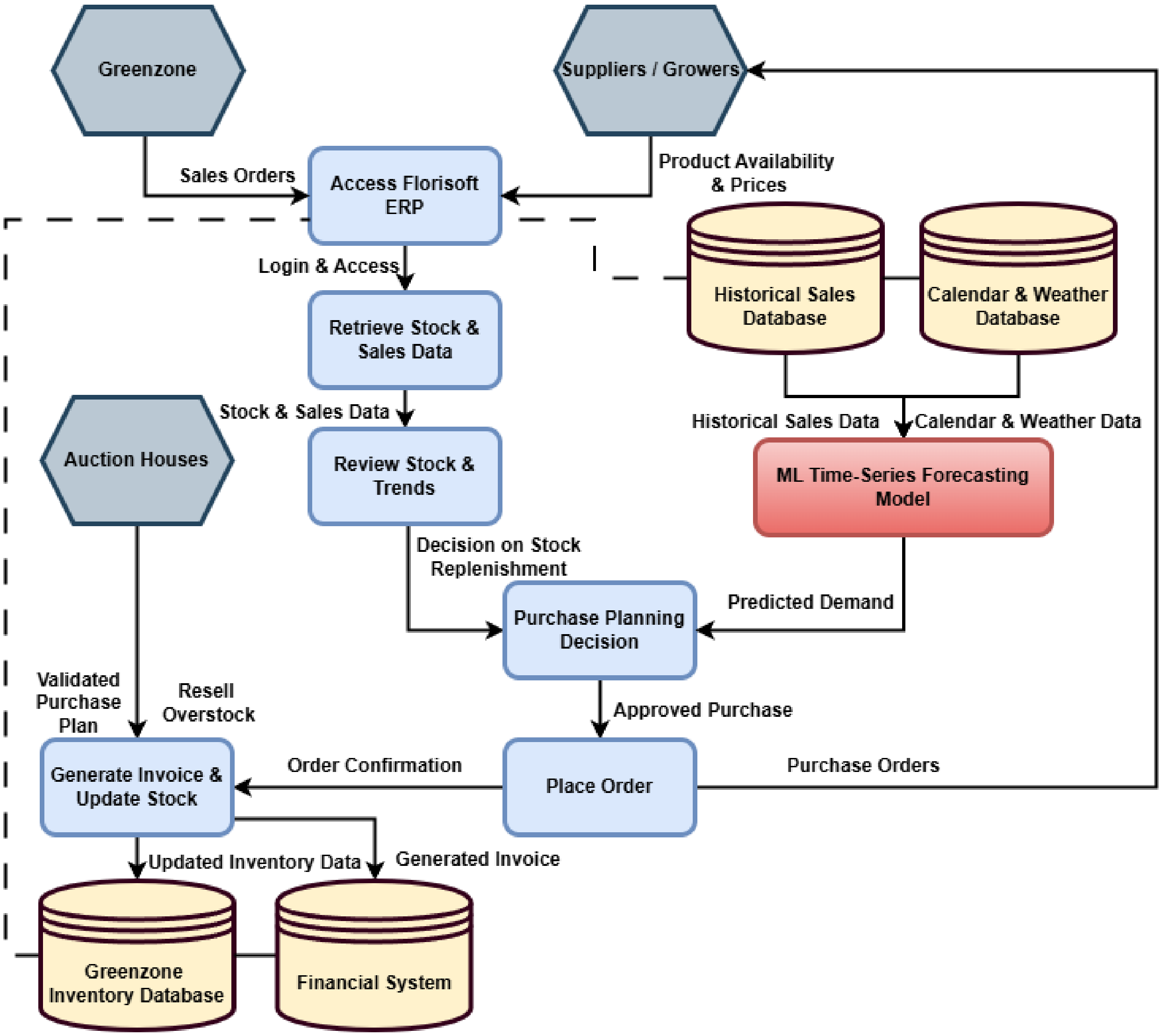

Figure 17 | Proposed Data Flow Diagram for Company B

Organizational & Cultural Readiness

To improve organizational and cultural readiness for ML adoption, Company B must strengthen leadership engagement and establish a structured change management approach, both of which are essential for embedding ML into the company's operational environment and long-term strategic direction. These efforts must directly support the transformation of the purchase planning process, ensuring that the organizational foundation is aligned with technical implementation.

Leadership involvement must begin with the articulation of ML's strategic relevance to the company's logistics functions. Management must publicly endorse the initiative, allocate modest financial and personnel resources, and actively integrate ML into the firm's innovation roadmap. This may include assigning an internal staff member to coordinate with external support in piloting a forecasting model, setting aside funds for data readiness efforts, or incorporating ML-related objectives into business planning cycles. Visible commitment signals organizational seriousness and fosters legitimacy for ML experimentation.

Equally important is the development of a basic but coordinated change management plan. Such a plan must outline the specific objectives for ML use in purchase planning, assign responsibilities for each step, and define internal communication strategies. For example, an IT-literate employee may be tasked with preparing the necessary data, while a process coordinator oversees pilot activities. Regular updates, short team briefings, or shared documents should be used to keep staff informed and involved.

Resistance to change must also be anticipated. Employees may fear disruption, misunderstand the purpose of ML, or question its practical value. These concerns must be addressed proactively by providing clear, transparent communication, assuring staff of job security, and introducing targeted training to demystify ML use. By fostering inclusion and open dialogue, trust can be strengthened and operational resistance reduced.

Business Process Readiness

To strengthen its business process readiness for ML integration, Company B must establish a structured, reliable, and data-compatible operational environment. This includes formalizing workflows, embedding mechanisms to address inefficiencies, automating critical operations, promoting data-driven decision-making, and instituting performance monitoring practices. These improvements support the transformation of the company's purchase planning process, enabling consistency, traceability, and transparency, all of which are prerequisites for the effective application of ML forecasting models. The foundation lies in process standardization. Company B should document the actual steps undertaken during purchase planning, capturing existing routines, including informal practices. These process maps should be accessible, routinely updated, and clearly communicated to all relevant personnel. Such documentation ensures execution consistency across departments and timeframes, reducing ambiguity and enabling reliable data capture for predictive modelling.

With standardized workflows in place, Company B must embed structured routines for identifying and resolving operational inefficiencies. This includes defining common deviations, such as order quantity mismatches or stock data corrections, and introducing clear response protocols for each scenario. These should be included in existing workflow documentation and reviewed regularly. This approach reduces performance variability and supports the creation of cleaner datasets, suitable for ML model development. Following this, automation should be selectively introduced to replace repetitive, error-prone manual tasks. Activities such as inventory reconciliation, purchase status tracking, or internal coordination should be supported by scalable, lightweight tools. Barcode-based systems or calendar-driven scheduling software can be deployed incrementally without requiring large-scale investment. Automation ensures that data is captured in a timely, structured manner, while freeing human resources for higher-value tasks.

The most pressing area for improvement, however, lies in fostering data-driven decision-making, where Company B scored at Level 1, the lowest maturity level across all assessed categories. This result underscores a complete absence of structured data support in planning activities, with decisions made primarily based on individual judgment or informal communication. To address this, Company B must introduce visual dashboards that provide key decision-makers with real-time or regularly updated information on stock levels, purchasing cycles, supplier reliability, and order accuracy. These dashboards must be embedded into daily planning routines, enabling decisions to be informed by concrete operational data rather than anecdotal input. Doing so will not only improve short-term performance but also create a data feedback loop essential for future ML applications.

Finally, performance monitoring should be integrated as a continuous process. Key performance indicators related to purchase planning, such as order accuracy rates, average stock turnover, or frequency of urgent orders, should be clearly defined, tracked, and reviewed periodically. Regular review sessions should be conducted to interpret deviations, refine practices, and prepare the organisation for more advanced data-enabled decision-making. These efforts will collectively strengthen Company B's business process readiness and support a smoother transition toward ML-supported planning.

Strategic Alignment

To be considered strategically aligned for ML adoption in the context of the purchase planning process, Company B must ensure that its implementation approach reflects operational needs, financial capacity, environmental considerations, and competitive positioning. Strategic alignment begins with selecting a targeted ML use case that offers tangible business value. The purchase planning process was chosen due to its central role in inventory management, its vulnerability to overstocking, and its reliance on data that is already partially available. This process exhibits characteristics suitable for ML intervention, such as recurring decision points, measurable outputs, and a high degree of influence on operational efficiency.

A structured method for identifying and prioritizing ML use cases must be applied as Company B explores further adoption. Each candidate use case should be evaluated based on data availability, operational importance, and implementation feasibility. In the case of purchase planning, the presence of historical sales data and structured procurement patterns supports the use of forecasting models. External stakeholders, such as software vendors or university partners, may assist in piloting, but Company B must retain ownership of the use case definition, data boundaries, and evaluation criteria to ensure alignment with its internal processes. It is essential that ML deployment is targeted toward a well-defined operational process where predictive modelling can deliver measurable improvements. In the case of Company B, the purchase planning process has been selected as the most suitable domain for ML integration. This process directly affects inventory levels, procurement efficiency, and cost optimization, making it a high-impact area for data-driven forecasting. To illustrate how the proposed ML model would be integrated and utilized within this workflow, Figure 18 presents a use case diagram outlining the interactions between key roles and the demand forecasting system. The diagram highlights critical tasks such as generating forecasts, validating outputs, and applying insights to procurement planning, while also reflecting the supporting data architecture. This visual representation clarifies the operational relevance of ML and facilitates understanding of its role in enhancing decision-making and data quality across the purchase planning process.

Competitive benchmarking can enhance this alignment by informing Company B of how similar organizations integrate ML into their supply chain and procurement workflows. This information can be collected through sector-specific case studies, vendor documentation, or engagement with innovation platforms. Benchmarking does not imply imitation but supports informed decision-making by identifying relevant practices and helping to set realistic expectations for impact and scalability. In parallel, Company B should define a clear financial framework for its ML initiatives. The budget for purchase planning optimization must cover essential components such as data cleaning, tool licensing, external support, and limited infrastructure upgrades. Expectations regarding return on investment should be stated before deployment. For example, the use of ML in purchase forecasting is expected to reduce stock surplus and improve procurement timing. These expectations must be documented, monitored throughout the pilot, and used to support decisions about expanding ML applications.

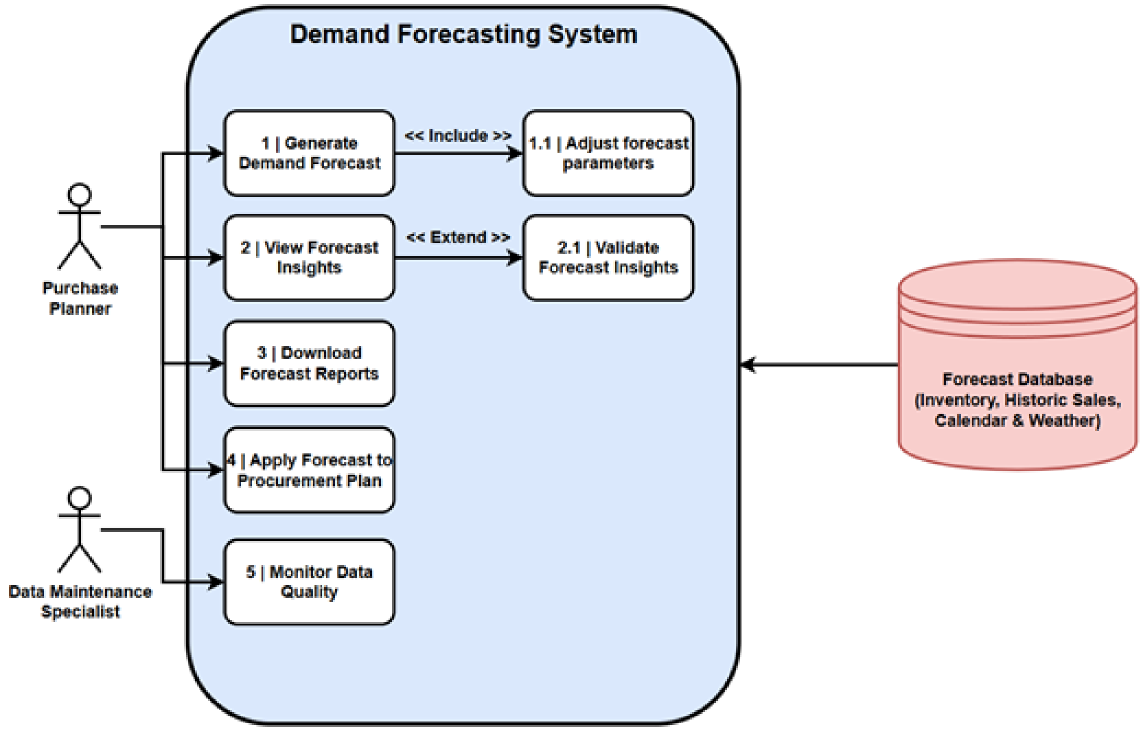

Figure 18 | Use Case Diagram of the Optimized Purchase Planning Process

Sustainability considerations should also inform strategic planning. Within the purchase planning process, ML can help reduce spoilage and limit unnecessary procurement, directly contributing to waste reduction and resource efficiency. Such alignment with environmental goals enhances the broader value proposition of the ML initiative. Opportunities to collaborate with partners focused on sustainable logistics or digital innovation should be explored to access funding and expertise. In this way, the strategic integration of ML in purchase planning can deliver operational, financial, and environmental benefits, positioning Company B for more confident and effective scaling in the future.

Security & Regulatory Compliance

Within the security and regulatory compliance category, Company B demonstrates satisfactory performance in access control and data protection but requires further enhancement in cybersecurity measures to ensure the secure deployment of ML tools. While mechanisms such as multi-factor authentication and role-based access control are already implemented effectively, as depicted in the proposed security architecture in Figure 19, the broader cybersecurity posture remains underdeveloped. In particular, Company B should formalize a cybersecurity policy outlining responsibilities, protection areas, and response procedures. This includes ensuring the activation of firewall protection on all systems, conducting regular software updates, and implementing lightweight vulnerability scanning tools on a quarterly basis. The architecture also recommends secure API communication using OAuth2 protocols, encryption standards such as TLS and AES-256, and embedded controls including anomaly detection and rate limiting. These measures together establish a secure environment for ML integration, minimizing exposure to external threats while maintaining system resilience and data integrity. By adopting this architecture and reinforcing its cybersecurity foundations, Company B can more confidently support the operational scaling of ML applications within its purchase planning process.

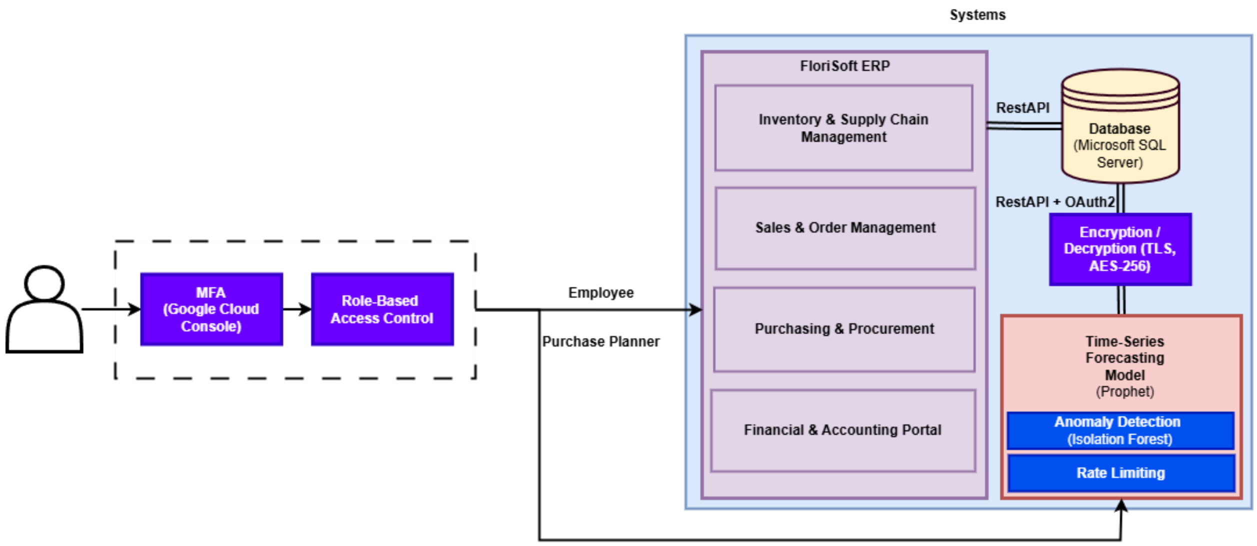

Figure 19 | Proposed Security Architecture for Purchase Planning Process

External Dependencies & Ecosystem Readiness

To strengthen readiness in the category of external dependencies and ecosystem integration, Company B must cultivate strategic awareness and expand its engagement beyond internal systems and data. Three areas are critical to this effort: awareness of industry trends, incorporation of external data, and access to AI expertise. First, proactive engagement with sector-wide ML developments is essential to remain aligned with evolving client expectations and technology standards. Company B should introduce a lightweight but consistent mechanism to monitor innovation in the logistics sector, such as reviewing ML-focused newsletters, attending webinars, or recording benchmark observations from peer companies. These insights can be reviewed quarterly by management and operations teams to support timely decision-making and to identify emerging risks and opportunities. By comparing its digital trajectory against peers, Company B can better prioritize ML use cases that offer strategic differentiation.

Second, external data integration should be expanded to enhance the accuracy and responsiveness of ML initiatives. In the case of purchase planning, relevant variables include holiday schedules, weather conditions, and macroeconomic indicators. Company B is advised to incorporate publicly available data sources such as government datasets, weather APIs, or traffic feeds into its planning environment. This data can initially be imported manually or linked through simple scripts. Over time, integration may be automated as system maturity improves. By contextualizing internal records with real-world conditions, forecasting reliability and planning precision can be significantly improved.

Third, while Company B does not require in-house data scientists, access to external AI expertise is necessary to guide implementation. This can be achieved through short-term collaborations with academic institutions, consultants, or digitalization agencies. The objective is to secure technical support for use case framing, model development, and performance evaluation. Clear communication must be established between technical and operational roles to ensure that the solution addresses real process needs and remains usable in practice. Prior to engagement, Company B should prepare a concise internal brief describing the selected use case, available data, and desired outcomes. This ensures that external experts can work effectively and within realistic constraints.

Scalability & Long-Term Viability

To ensure readiness in the category of scalability and long-term viability, Company B must adopt practices that support the sustainable growth of ML applications beyond initial deployment. This includes measures to optimize ongoing costs and establish clear routines for maintaining and updating deployed models.

First, cost optimization is essential to ensure that ML remains financially viable as implementation progresses. Company B should identify and document all cost components associated with the forecasting model proposed for the purchase planning process. This includes direct costs such as software licenses, cloud computing usage, and technical consultation, as well as indirect costs like staff time required for model supervision or data preparation. These costs should be monitored regularly, ideally as part of quarterly planning routines. Adjustments can then be made to eliminate inefficient resource use, such as excessive model retraining or over-provisioned infrastructure. Gradual scaling based on proven impact is advised, focusing resources on high-value use cases while deferring broader expansion until performance and budget permit. Where possible, Company B should also explore public funding options or academic partnerships to reduce internal financial burden.

Second, a structured yet lightweight approach to model maintenance must be implemented. ML models used in forecasting are prone to performance degradation due to shifting demand patterns, seasonal fluctuations, or changes in procurement policies. To address this, performance indicators such as forecast accuracy or inventory alignment should be tracked at regular intervals. Clear thresholds must be set to determine when retraining is necessary, and responsibilities for monitoring and updating the model should be formally assigned. All model versions must be documented using a consistent naming convention and stored along with metadata that outlines training parameters, datasets, and deployment dates. If external developers are involved, contractual agreements must ensure full transfer of versioned and reproducible models.

Before applying any new model version, a testing phase must confirm performance stability and alignment with operational needs. For instance, side-by-side comparisons of forecast results or limited rollouts can help confirm the value of updates while minimizing disruption. These efforts together will allow Company B to transition from experimental use of ML to a scalable, manageable, and sustainable operational capability.

I3) Transport Planning Optimization at Company C

Introduction of Problem and Process Selection

To examine the application of the proposed MLPRALS framework within a real-world logistics context, the transport planning process of Company C is selected as a case study. This selection is based on the process's centrality to the company's daily operations and its strategic importance in ensuring cost efficiency and service quality. The current transport planning process, depicted in Figure 20, exhibits a range of structural limitations that hinder its responsiveness, scalability, and adaptability in dynamic delivery environments.

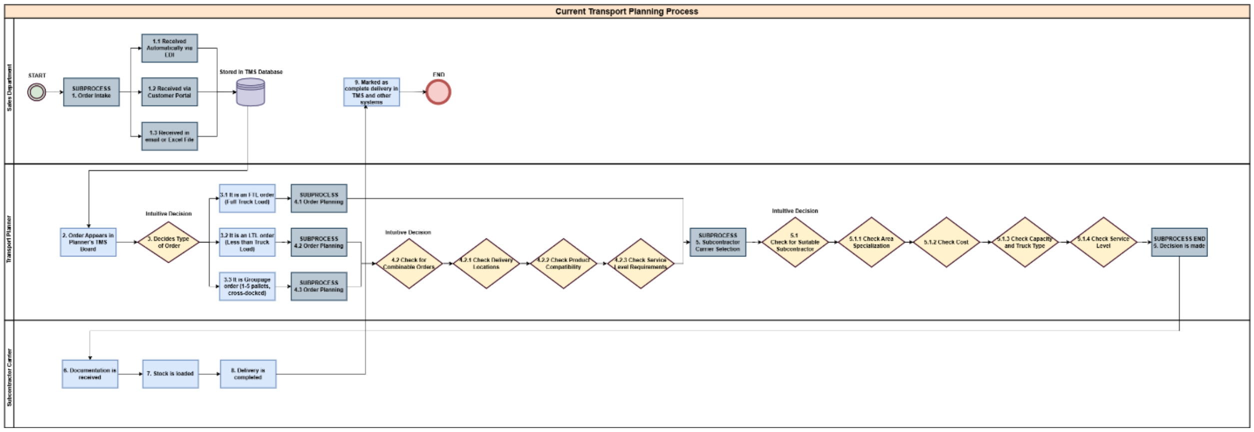

Figure 20 | Current Transport Planning Process at Company C

At present, routing and vehicle assignment decisions are carried out manually by planners relying on static schedules, subjective judgment, and basic ERP data exports. Real-time variables such as traffic patterns, delivery constraints, or driver availability are only partially accounted for, and adjustments are made reactively rather than through anticipatory planning. These limitations reduce operational efficiency and contribute to suboptimal route selection, underutilization of available transport capacity, and delayed deliveries. Additionally, route planning lacks integration with feedback loops from previous performance data, which restricts learning from past inefficiencies and prevents iterative process improvement.

Another critical weakness lies in the absence of adaptive mechanisms for coordinating multiple delivery constraints simultaneously. These include vehicle capacity, service windows, customer priorities, and geographical clustering. Without algorithmic support, planners are unable to optimize these factors holistically, resulting in higher fuel costs, inconsistent delivery quality, and increased scheduling effort. Moreover, coordination between planners, dispatchers, and warehouse personnel is fragmented, further delaying decision-making and increasing the likelihood of miscommunication or planning errors. To address the limitations identified in the current transport planning process at Company C, an ML-optimized process has been developed. Based on the suitability of the evaluated ML methods, paradigms, and algorithms presented in the comparative analysis of this study, reinforcement learning has been selected as the most appropriate method for optimization. A reinforcement learning model is integrated into the optimized transport planning process, depicted in Figure 21, fundamentally improving key operational steps.

The new model replaces the manual, experience-based approach that characterized the current process, particularly in shipment grouping and subcontractor allocation. Instead of relying on individual planner intuition, the model proposes optimal shipment combinations and subcontractor assignments by continuously learning from historical transport data, subcontractor performance records, and delivery outcomes. This transformation allows for enhanced trailer utilization, better carrier selection, and proactive disruption management, all contributing to reduced operational variability and increased scalability. This assessment identifies existing gaps across critical readiness categories and provides targeted guidance aimed at maximizing the operational and strategic benefits of ML adoption. The structured approach ensures that Company C can systematically strengthen its technological foundation and organizational capabilities to fully realize the potential offered by reinforcement learning integration.

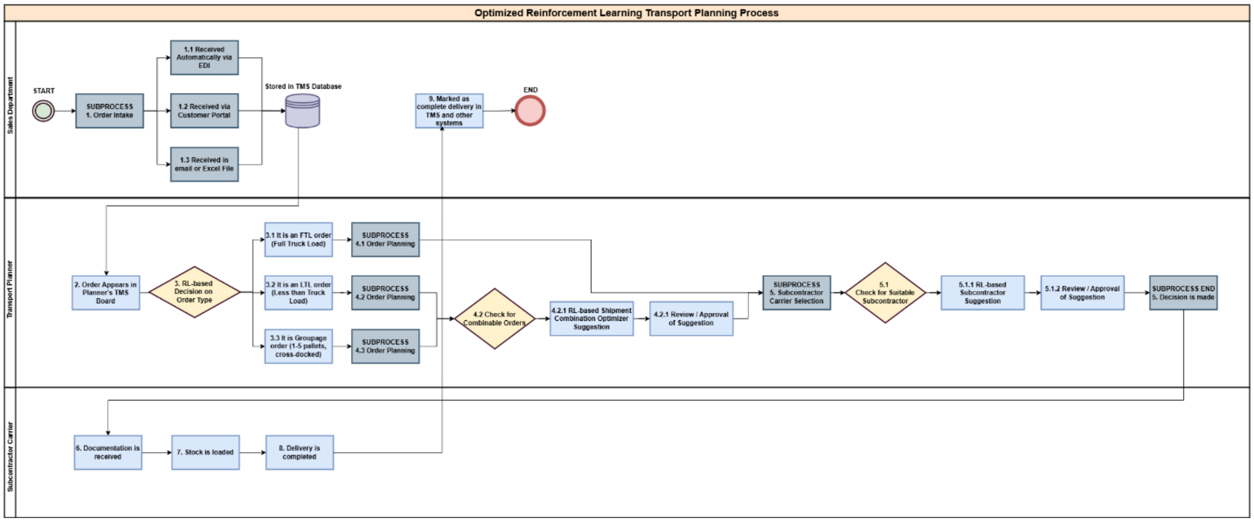

Figure 21 | Optimized Transport Planning Process at Company C

Readiness Score MLPRALS Framework

The category-level readiness score of Company C is presented in Figure 22, with detailed results provided in Table 32. According to the MLPRALS framework, Company C does not fully meet the required thresholds for ML readiness. To be considered ML-ready, an organization must achieve at least level 3 across all assessed categories, including a minimum of level 4 in data readiness. Although Company C demonstrates stronger performance in several areas compared to the other participating companies, its current scores still fall below the necessary criteria for immediate ML integration within its transport planning process.

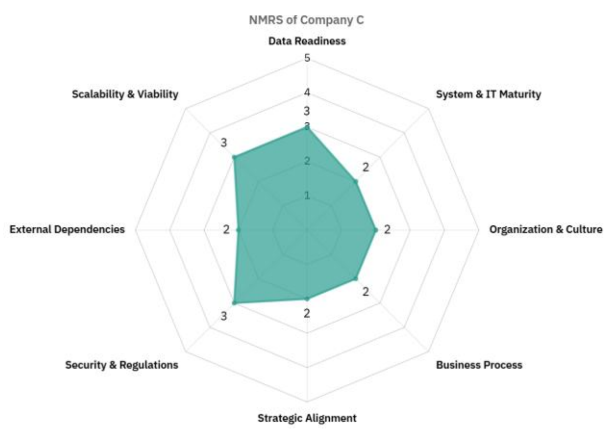

Figure 22 | Readiness Score Company C

Targeted Guidance MLPRALS Framework

Following the analysis of the readiness score of Company B, tailored guidance is provided to support the application of the MLPRALS framework to Company B's purchase planning process and their overall ML readiness, while bridging the gap between the current and desired state of the process.

Data Readiness

To support the readiness of Company C for ML adoption within the transport planning process, improvements in data readiness must be addressed with particular focus on data storage and data integration. Although Company C possesses foundational systems such as a TMS and a CRM platform, operational data remains scattered across multiple environments. This fragmentation impedes real-time decision-making, undermines data reliability, and complicates the application of advanced ML techniques.

To resolve these challenges, it is advised that Company C consolidates all critical logistics and transport planning data into a centralized digital environment. Although an ERP system is not currently deployed, the existing TMS and CRM platforms offer a potential foundation for consolidation, provided that structured data management practices are introduced. Historical transport orders, vehicle dispatch records, delivery confirmations, and client communication logs must be digitized where necessary and integrated into a consistent storage environment. The TMS should serve as the primary system of record, ensuring that all operational data relevant to route planning, load assignments, and transport performance is recorded systematically and remains accessible across relevant departments.

The transition toward centralized storage begins with a structured inventory of existing datasets, identifying where critical information resides, how it is updated, and how it can be migrated or linked. Data standardization must accompany this effort, with clear alignment of field names, consistent use of identifiers such as shipment numbers, and harmonization of formats across sources. Migration templates, data dictionaries, and field mapping exercises must be introduced to support this transition.

Beyond centralized storage, data integration represents a critical requirement given the dynamic nature of transport planning activities at Company C. It is essential that the TMS and CRM platforms be configured for seamless data exchange. Shared identifiers, such as order IDs or customer reference numbers, must link operational workflows across systems. Where direct system-to-system integrations are not immediately feasible, structured exports and scheduled imports should be implemented, ensuring that updates in one system are reflected in others without delays or inconsistencies.

To further enhance data readiness for ML integration in Company C's transport planning process, an optimized relational data structure is proposed, illustrated in Figure 23. This structure connects shipment details, goods-level data, and historical performance into a centralized, consistent format. It addresses current fragmentation across TMS and CRM systems and improves data quality through standardization. The schema enables continuous feedback, supports reinforcement learning, and facilitates more accurate and automated planning. By adopting this structure, Company C creates a reliable foundation for scalable and data-driven transport optimization.

Given the importance of real-time responsiveness in transport planning, Company C should prioritize the progressive automation of data synchronization between its systems. Middleware solutions, lightweight API connectors, or script-based data bridging can be explored to facilitate near-real-time information flows. This ensures that when delivery schedules shift, new orders are placed, or customer requirements change, planners receive timely and accurate updates without manual reconciliation efforts.

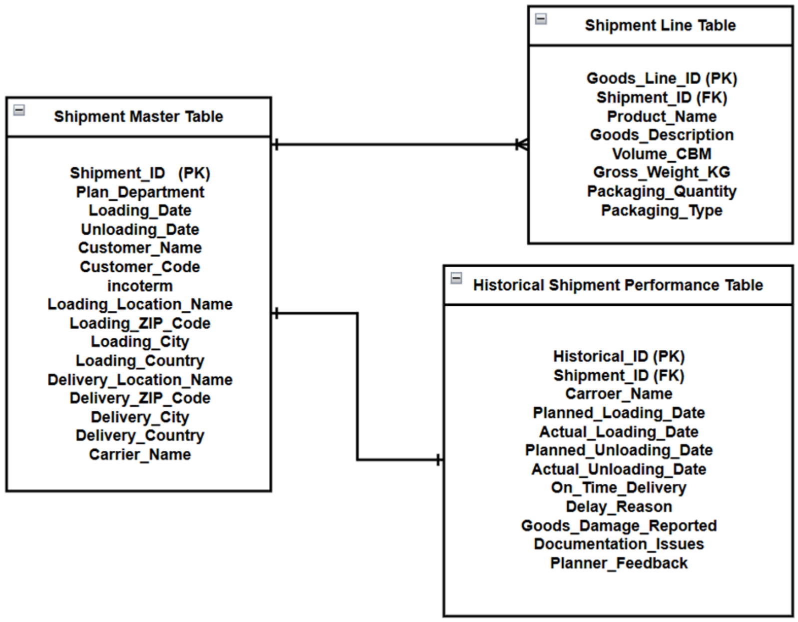

Figure 23 | Proposed Optimized Data Structure Company C

System & IT Maturity

To support the future integration of ML into its transport planning process, Company C must formalize its IT adaptability and future readiness efforts. Although the TMS and CRM platforms currently in use are updated annually and remain operationally sufficient, the absence of a structured roadmap could hinder scalability as technological requirements increase. Given that transport planning represents a strategic digitalization priority, proactive infrastructure planning is essential. Company C should begin by auditing its IT environment, focusing on software update histories, vendor support statuses, and integration capacities. Based on this audit, a two-to-three-year roadmap should be developed, identifying milestones such as enabling ML-compatible features, investing in cloud services, and improving system interoperability. The internal IT department should oversee this roadmap to ensure that investments align with transport planning optimization goals.

In parallel, regular monitoring of sector-specific technological trends must be introduced. This would allow Company C to anticipate emerging innovations and adapt its systems accordingly. A formalized policy for reviewing and refreshing systems, particularly after five years of use or loss of vendor support, should also be established. By implementing these measures, Company C will ensure that its transport planning operations remain secure, interoperable, and progressively more supportive of ML-based improvements. The optimized data flow diagram presented in Figure 24 introduces a more structured and interconnected architecture for the transport planning process at Company C. By centralizing data exchange among the TMS, CRM system, inventory database, subcontractor database, and historical order records, the model ensures that all operational decisions are informed by complete and consistently formatted information. The integration of these platforms eliminates the fragmentation currently caused by scattered and partially automated data handling, thereby improving internal coherence and enabling real-time data access across functions.

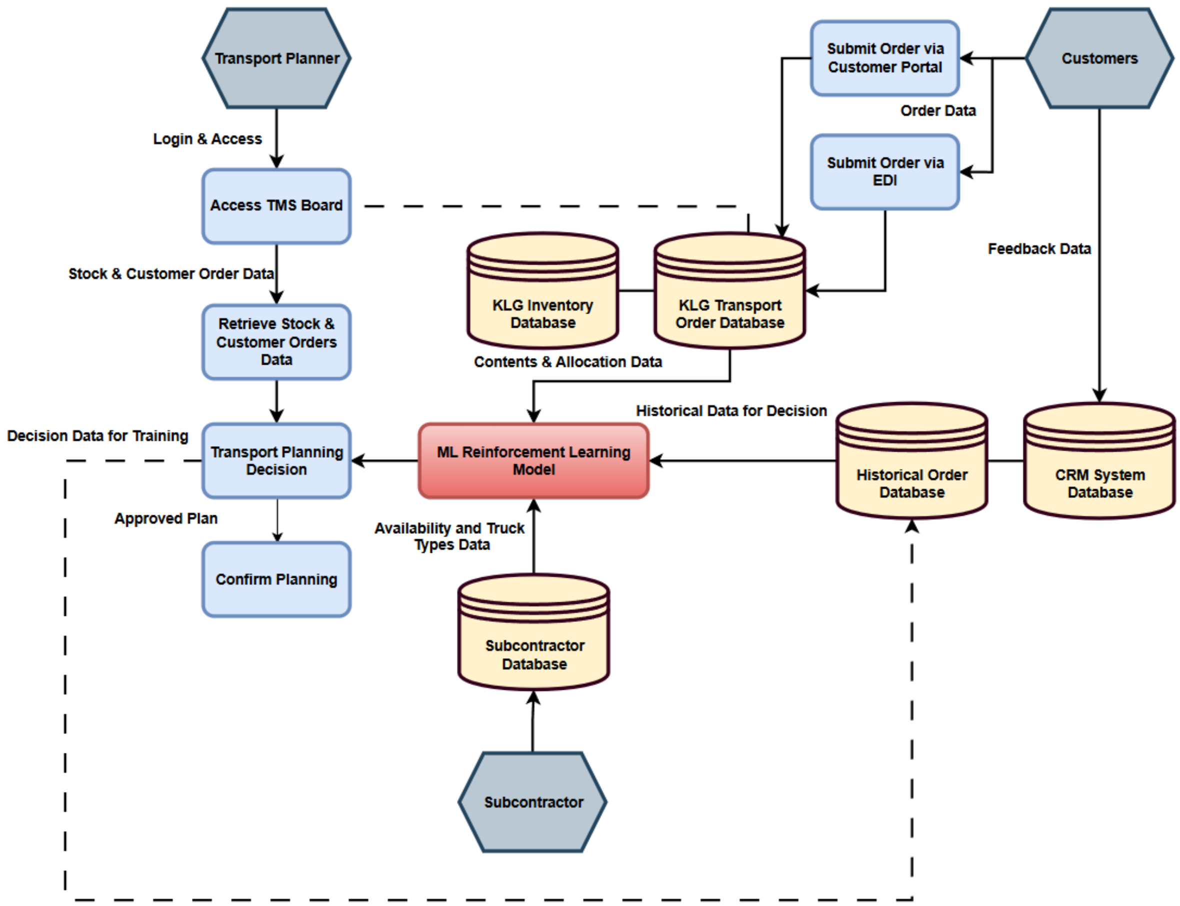

Figure 24 | Proposed Data Flow Diagram for Company C

In this setup, the reinforcement learning model benefits from continuous, structured input streams sourced from both planning outcomes and operational databases. This configuration allows for the automatic ingestion of historical orders, customer requirements, and subcontractor availability, which together enhance the model's contextual awareness and decision quality. Furthermore, the model's outputs are seamlessly fed back into the planning process, closing the loop between decision-making and learning. As a result, Company C can achieve higher planning efficiency, improved responsiveness to customer constraints, and more accurate allocation of logistics resources, all while maintaining traceability and system-wide alignment.

Organizational & Cultural Readiness

While Company C demonstrates interest in operational improvement at the management level, limited engagement exists among frontline transport planners in proposing or evaluating changes to planning workflows. To strengthen organizational and cultural readiness for ML adoption, particularly within the context of transport planning, structured mechanisms should be introduced to include employee insight in technology-related discussions. Although transport planners are currently not involved in improvement-oriented dialogue, their operational knowledge remains critical for identifying inefficiencies and validating ML-supported interventions.

It is therefore advised that Company C builds on its existing internal communication channels to establish formal feedback loops. These may include regular agenda points in team meetings where planning staff can reflect on recurring challenges or propose refinements to planning sequences. Low-effort digital feedback forms can be used to collect observations on scheduling delays, subcontractor mismatches, or inconsistent input data. Prompt questions such as "What planning step causes the most uncertainty each week?" or "Where is too much time spent deciding?" may encourage useful contributions.

To overcome the observed reluctance among lower-level staff, management should clearly communicate that ML technologies are intended to support, not replace, existing roles. Using sector-relevant examples, such as forecasting load constraints or recommending subcontractor allocation, can help demystify the technology and reduce resistance. When employee suggestions are gathered, one low-cost idea, such as digitizing feedback from missed deliveries, should be selected and tested as a pilot. Including the original proposers in this test phase allows them to validate the tool's accuracy, offer contextual input, and gain familiarity with the system. Recognizing contributors in internal updates and transparently linking their input to improved outcomes helps cultivate a participatory culture. Over time, this feedback loop reinforces a sense of ownership, encourages further engagement, and prepares the workforce for deeper integration of ML tools into the transport planning environment. This approach also strengthens the practical relevance of ML by ensuring models are grounded in day-to-day realities observed by staff closest to the process.

Business Process Readiness

For Company C to advance the ML readiness of its transport planning process, improvements are needed in the areas of process standardization, automation maturity, and the expansion of data-driven decision-making practices. Although core transport planning procedures are already formally documented at Company C, the integration of an ML solution demands further refinement. Process documentation must evolve beyond general descriptions toward detailed, step-by-step operational mappings that capture actual behaviors, deviations, and informal decision rules applied during planning activities. Given that transport planners currently act independently with supervisory involvement only during exceptions, it is essential that documentation reflects both standard workflows and established escalation procedures. This level of precision will support ML model training by providing clearer mappings between operational inputs and outcomes, reducing noise and inconsistencies in process data.

In terms of automation maturity, Company C has already made important progress through the use of their TMS, which distributes tasks via individual planners' digital dashboards. However, planning still relies heavily on manual coordination through calls. To further increase ML compatibility, the company should enhance automation at the information exchange level, ensuring that vehicle availability, route changes, and dispatch statuses are automatically updated and integrated into the TMS without requiring verbal confirmation. This improvement would eliminate avoidable lags, reduce reliance on subjective judgment, and provide more structured data for future reinforcement learning models to utilize during training and adaptation phases.

With respect to data-driven decision-making, Company C demonstrates a strong foundation through the use of KPI dashboards. Nevertheless, dashboard insights must be more systematically integrated into routine planning decisions rather than serving as occasional references. It is advised that planners begin each planning cycle with a structured dashboard review, using data points such as delivery punctuality, vehicle utilization rates, and deviation frequencies to inform task prioritization and routing strategies. Moreover, critical anomalies identified on dashboards should trigger predefined corrective actions rather than ad hoc responses. To institutionalize this, a short handbook linking key dashboard indicators to planning decisions could be developed internally, reinforcing the consistent use of data to guide operations.

Strategic Alignment

To support the strategic alignment of its transport planning operations, Company C is advised to formalize its competitive benchmarking activities. Although informal comparisons with peer companies are already conducted, these efforts lack the structure needed to guide investment decisions and ML adoption priorities. By developing a more systematic approach, the company can identify where ML is already being applied in the logistics sector and how its own practices compare. Relevant focus areas include shipment optimization, subcontractor assignment, and predictive scheduling, all of which remain manually executed in Company C's current process.

Existing partnerships with universities may be used to access sector reports or conduct targeted comparisons, while participation in logistics innovation forums can offer practical insights into how ML is being used by competitors. These findings should inform internal discussions about the positioning of Company C's ML pilot, which introduces a reinforcement learning model into the transport planning workflow. As depicted in Figure 25, this model supports planners with order classification, shipment combination evaluation, and subcontractor ranking suggestions. Benchmarking results can help validate these features and highlight additional opportunities for differentiation.

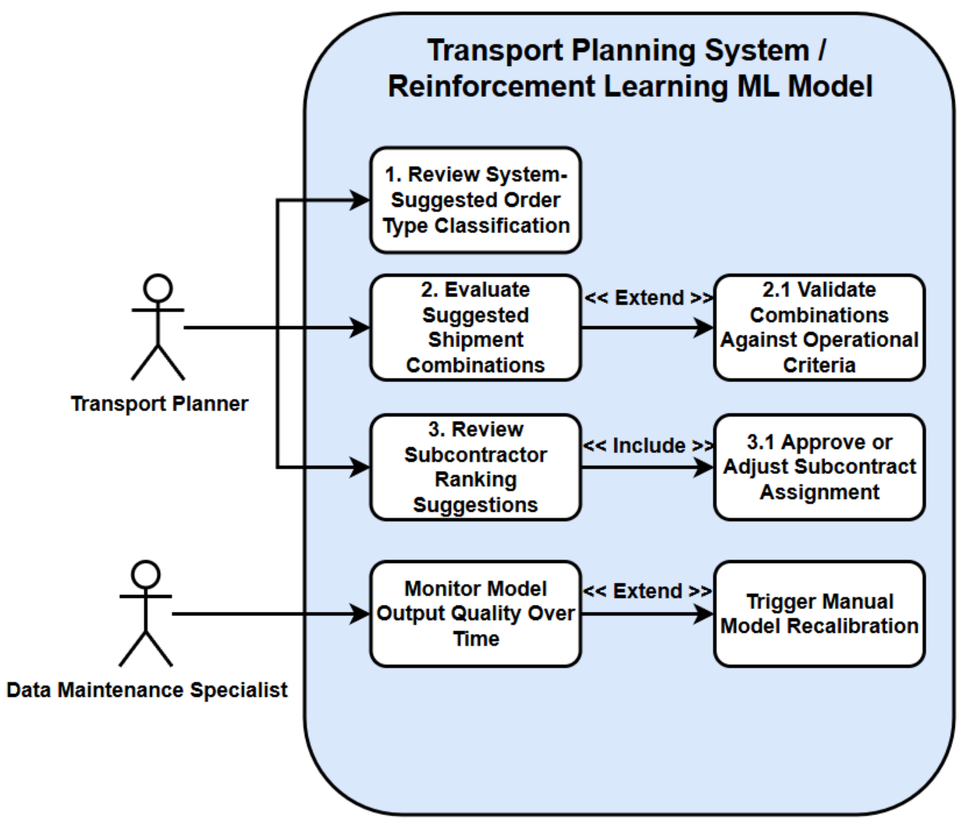

Figure 25 | Use Case Diagram of the Optimized Transport Planning Process

Security & Regulatory Compliance

Company C is assessed as security-ready within the scope of the MLPRALS framework, having implemented key mechanisms such as multi-factor authentication and role-based access control for internal and subcontractor access. However, while these measures provide a solid baseline, further enhancement is recommended through the adoption of an optimized security architecture tailored to the integration of ML into the transport planning process.

The proposed architecture, illustrated in Figure 26, introduces several critical improvements. It formalizes the segmentation of access control across stakeholders, enforces token-based authentication and IP whitelisting for external partners, and ensures encryption of all sensitive communications and stored data using TLS and AES-256 standards. Additionally, it incorporates audit logging and validation layers around the ML environment to ensure secure, monitored interactions between the reinforcement learning model and operational data systems.

This architecture improves the resilience of Company C's digital infrastructure by reducing vulnerability at data exchange points and maintaining strict control over user access to ML outputs. It also prepares the environment for scalable deployment, where multiple systems and actors interact with predictive tools without compromising data integrity or exposing the organization to compliance risks. As Company C advances its ML adoption, this framework enables the secure integration of external data sources and safeguards sensitive operational records, thus supporting a trusted foundation for long-term digital transformation.

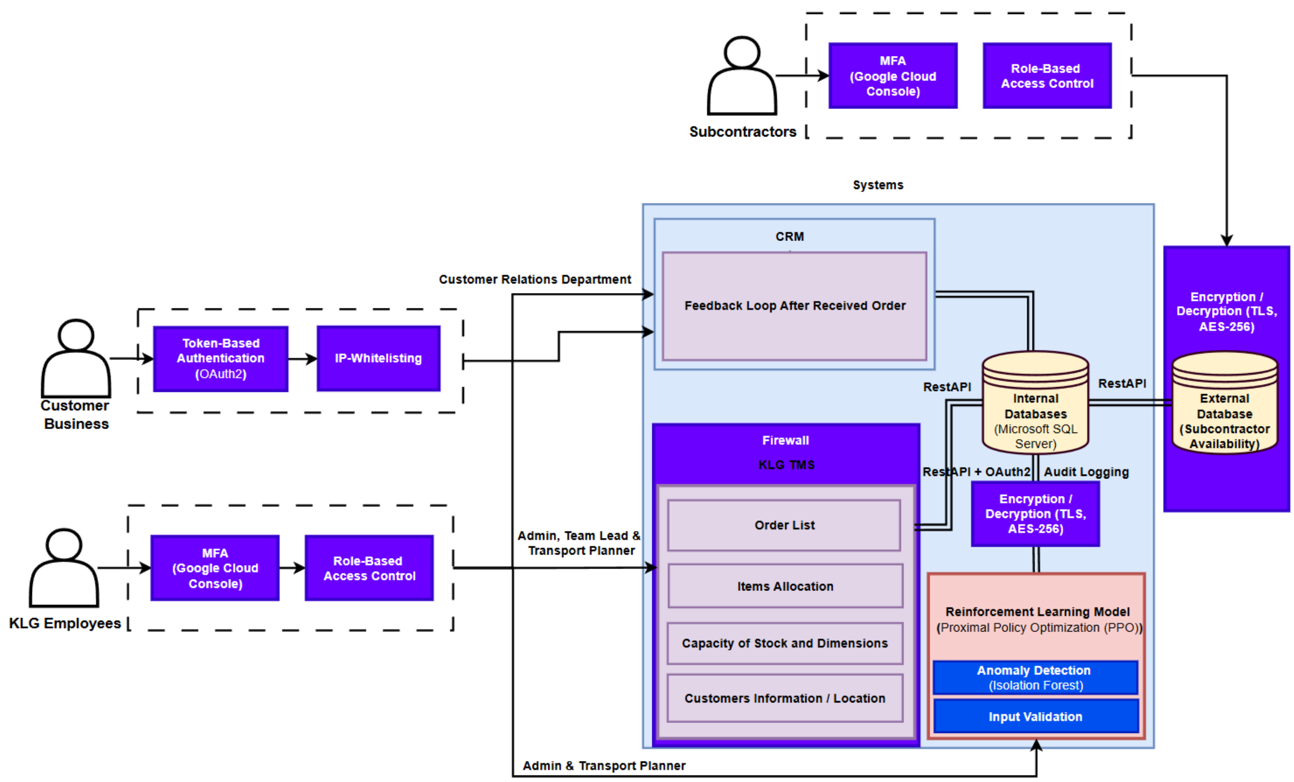

Figure 26 | Proposed Security Architecture for Transport Planning Process

External Dependencies & Ecosystem Readiness

Company C is considered partially aligned with the expectations outlined under the external dependencies and ecosystem readiness dimension of the MLPRALS framework. Although the company benefits from internally managed IT infrastructure and vendor contracts that are facilitated through external providers, critical limitations persist in system interoperability and the integration of external data. These constraints reduce the feasibility of advanced ML applications such as reinforcement learning in transport planning.

With respect to vendor IT maturity, Company C currently collaborates with external IT providers. However, the associated systems do not allow for structured interoperability. While API functionality is technically available, the systems are not configured to support real-time data exchange, and relevant data remains siloed. This leads to continued reliance on static workflows and increases the need for manual coordination across platforms. To address this, Company C should establish a formal protocol for evaluating vendors, which must include requirements for ML readiness, compatibility with standard export formats, and transparency in data documentation. The internal IT team should work closely with vendors to ensure that API endpoints are accessible, data schemas are clearly defined, and integration with key internal platforms, especially the TMS, is prioritized to support automated data flows.

Moreover, Company C currently lacks any systematic incorporation of external contextual data into transport planning decisions. Although regional performance is reviewed manually, there is no use of external signals such as real-time traffic data, weather disruptions, or fuel price trends. This significantly limits the contextual awareness of the planning process. As the reinforcement learning model matures, it will benefit from the inclusion of dynamic external inputs that help to explain shipment delays, regional disruptions, or subcontractor constraints. It is therefore advised that Company C begin by identifying a small number of relevant and accessible external data sources. These may include open traffic APIs, regional weather updates, or public logistics datasets. Initial integration can be achieved through low-complexity solutions such as manual imports or simple scripting. Once implemented, these external inputs can be progressively incorporated into planning dashboards or model training datasets.

By improving alignment with vendor systems and gradually incorporating external data, Company C will enhance the maturity and responsiveness of its digital ecosystem. These changes are expected to increase the accuracy, relevance, and operational value of ML-supported decision-making. Strengthening these areas will also ensure that future ML initiatives are grounded in a more connected and adaptive digital infrastructure.

J) Detailed Readiness Index Results

ML Preparation & Readiness Assessment Logistics SME Framework

After answering the concept questions within the proposed framework, the detailed results for the assessment are presented in Table 32.

Table 32 | Detailed Assessment Results of ML Preparation & Readiness Assessment Logistics SME Framework

Questions / Answers	Company A	Company B	Company C
Category A: Concept 1	Level 4	Level 3	Level 4
Category A: Concept 2	Level 4	Level 4	Level 3
Category A: Concept 3	Level 4	Level 3	Level 4
Category A: Concept 4	Level 4	Level 3	Level 3
Category A: Concept 5	Level 4	Level 3	Level 4
Category A Level R_k	**Level 4**	**Level 3**	**Level 3**
Category B: Concept 1	Level 3	Level 2	Level 3
Category B: Concept 2	Level 3	Level 3	Level 3
Category B: Concept 3	Level 3	Level 2	Level 3
Category B: Concept 4	Level 2	Level 3	Level 2
Category B: Concept 5	Level 3	Level 3	Level 3
Category B Level R_b	**Level 2**	**Level 2**	**Level 2**
Category C: Concept 1	Level 3	Level 2	Level 3
Category C: Concept 2	Level 2	Level 3	Level 3
Category C: Concept 3	Level 3	Level 2	Level 3
Category C: Concept 4	Level 2	Level 3	Level 2
Category C: Concept 5	Level 3	Level 3	Level 3
Category C Level R_c	**Level 2**	**Level 2**	**Level 2**
Category D: Concept 1	Level 2	Level 2	Level 2
Category D: Concept 2	Level 3	Level 2	Level 3
Category D: Concept 3	Level 3	Level 2	Level 2
Category D: Concept 4	Level 2	Level 1	Level 2
Category D: Concept 5	Level 3	Level 2	Level 3
Category D Level R_d	**Level 2**	**Level 1**	**Level 2**
Category E: Concept 1	Level 3	Level 2	Level 3
Category E: Concept 2	Level 2	Level 2	Level 2
Category E: Concept 3	Level 2	Level 2	Level 3
Category E: Concept 4	Level 3	Level 2	Level 3
Category E: Concept 5	Level 3	Level 3	Level 3
Category E Level R_e	**Level 2**	**Level 2**	**Level 2**
Category F: Concept 1	Level 3	Level 3	Level 3
Category F: Concept 2	Level 3	Level 2	Level 3
Category F: Concept 3	Level 3	Level 3	Level 3
Category F: Concept 4	Level 3	Level 3	Level 3
Category F: Concept 5	Level 3	Level 3	Level 4
Category F Level R_f	**Level 3**	**Level 2**	**Level 3**
Category G: Concept 1	Level 3	Level 3	Level 2
Category G: Concept 2	Level 3	Level 2	Level 3
Category G: Concept 3	Level 3	Level 2	Level 2
Category G: Concept 4	Level 3	Level 2	Level 3
Category G: Concept 5	Level 3	Level 3	Level 3
Category G Level R_g	**Level 3**	**Level 2**	**Level 2**
Category H: Concept 1	Level 3	Level 3	Level 3
Category H: Concept 2	Level 3	Level 3	Level 3
Category H: Concept 3	Level 3	Level 2	Level 3
Category H: Concept 4	Level 3	Level 2	Level 3
Category H: Concept 5	Level 3	Level 3	Level 3
Category H Level R_h	**Level 3**	**Level 2**	**Level 3**

By combining the levels across all categories for each company, the gathered temporary results are:

$$Temporary\ Result\ Company\ A = 4 + 2 + 2 + 2 + 2 + 3 + 3 + 3 = 21$$

$$Temporary\ Result\ Company\ B = 3 + 2 + 2 + 1 + 2 + 2 + 2 + 2 = 16$$

$$Temporary\ Result\ Company\ C = 3 + 2 + 2 + 2 + 2 + 3 + 2 + 3 = 19$$

To calculate the NMRS values, each score R_i from the eight readiness categories (rated on a 1-5 scale) is first transformed using the formula $\frac{R_i-1}{4}$. This operation converts each category score into a normalized value between 0 and 1. Division by four is applied because the proposed MLPRALS framework uses a five-level ordinal scale, where Level 1 represents the lowest readiness and Level 5 the highest. The total range of this scale is calculated as 5-1=4. To transform any score R_i from the original [1,5] range to a normalized [0,1] range, the minimum value (1) is subtracted, and the result is divided by the full range (4). The NMRS is then calculated by taking the arithmetic mean of these eight normalized values:

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

The process standardizes each category score and produces a continuous readiness indicator that ranges from 0.00 to 1.00. For Company A, a total score of 21 yields eight normalized values, each calculated as $\frac{R_i-1}{4}$, which are then averaged to give the NMRS values.

$$NMRS\ Company\ A = 0.406$$

$$NMRS\ Company\ B = 0.25$$

$$NMRS\ Company\ C = 0.344$$

Conceptual Framework Model for AI adoption in SMEs [59]

The process of normalization and collecting results from the framework is based on a pillar-by-pilar assessment to ensure clarity and completeness. The framework focuses on five pillars of readiness (Digital & Smart Factory, Data Strategy, Human Resources, Organization Culture, Organization Structure). Due to the academic nature of the original study, the full questionnaire is not published in a standalone format, but the structure and scoring method are described clearly. The proposed questions are carefully crafted to reflect the intent and categories of the original framework in a practically assessable form, suitable for conversation and scoring. To obtain normalized results while remaining consistent with the scoring logic defined in the original framework, weighted numerical values ranging from zero as answer A) to one hundred as answer E) in twenty-five value intervals, are assigned to each response option. Table 33 presents the method of assessment.

Table 33 | Readiness Assessment Structure of Conceptual Framework Model for AI Adoption in SMEs

Pillar	Question	Possible Answers
Smart Factory / Digital Infrastructure	**Digitalization of production / logistics processes**: Which of the following best describes your company?	A) No digital tools are used in production / logistics. B) Some digital tools are used but not integrated. C) Digital tools are used and partially integrated. D) Digitalization is widespread and mostly integrated. E) Fully Digital and integrated smart factory / logistics.
	Use of IoT, sensors, or other data-capturing systems: Which level best reflects your current use of real-time data collection systems?	A) Not used at all. B) Some devices with some integration. C) Several devices with some integration. D) Systematically used across operations. E) Fully integrated real-time feedback systems.
	Automation of processes: How automated are your operational tasks?	A) No automation in place. B) Some basic tasks automated. C) Partial automation in logistics / production. D) Majority of tasks automated. E) Advanced and adaptive automation systems.
Data Strategy	**Data availability and structure**: To what extent is operational data collected and structured in your organization?	A) Data is not systematically collected. B) Data is collected but unstructured or inconsistently stored. C) Data is structured in some departments or tools. D) Data is structured and centralized for internal use. E) Data is structured, integrated, and regularly used across the organization.
	Use of data for decision-making: How is data currently used in your company?	A) Rarely used. B) Used for occasional manual reporting. C) Used for regular performance tracking or dashboards. D) Actively used for decision-making across departments. E) Continuously used for predictive insights and planning.
	Data integration capability: How well can data be accessed or exchanged between systems or departments?	A) Not at all. B) Data sharing happens ad hoc and manually. C) Some systems are linked, but with delays or limitations. D) Systems are integrated and data flows automatically across key areas. E) Data integration is real-time, seamless, and supports external data inputs.
Human Resources and Digital Skills	**Digital competence of staff**: How would you describe the overall digital proficiency of your employees?	A) Very limited digital skills. B) Basic digital use (emails, spreadsheets, etc.) C) Comfortable with business software but limited data skills. D) Includes personnel familiar with data tools and digital platforms. E) Teams include staff with strong digital and analytical skills.
	Training and upskilling efforts: What kind of digital training has been offered in your organization?	A) No training offered. B) Informal internal discussions or peer learning. C) Occasionally structured training (e.g., webinars, workshops) D) Regular, formal training programs on digital tools or data use. E) Specific AI-related or data training programs involved.
	Collaboration between IT and operations: To what extent do IT and operational teams collaborate on technology use or digital improvement?	A) No collaboration. B) Minimal collaboration (ad hoc communication). C) Occasional coordination during digital tool use. D) Regular joint projects or shared responsibilities. E) Integrated teams working on digital and AI initiatives.
Organizational Structure	**Integration of digital goals into organizational structure**: To what extent are digital innovation goals embedded in your organizational planning?	A) No formal inclusion in planning or governance. B) Occasionally mentioned without clear structural ties. C) Included in plans but with limited structural responsibility. D) Clearly assigned to roles or departments. E) Fully integrated into governance and organizational structure.
	Role clarity for digital initiatives: Are responsibilities for digital initiatives clearly assigned within the organization?	A) No defined responsibilities exist. B) Informally assigned without documentation. C) Assigned as a secondary role (e.g., to existing managers) D) Assigned to specific role or small internal team. E) Assigned to a dedicated cross-functional team with clear mandates.
	Structural follow-up on digital progress: How does your organization evaluate progress structurally?	A) No evaluation or follow-up processes in place. B) Informal or ad hoc evaluations occasionally happen. C) Evaluation occurs occasionally but without clear criteria. D) Evaluations are scheduled and use key indicators. E) Evaluations are part of strategic reviews with actionable follow-up.
Organizational Culture	**Openness to AI exploration**:	A) No interest or awareness of AI potential. B) Some awareness but uncertain or skeptical attitudes. C) Moderate interest with occasional internal discussions.

	How would you describe your organization's attitude toward AI opportunities?	D) Clear interest with active exploration of AI use cases. E) High enthusiasm and proactive identification of opportunities.
	Initiative in AI experimentation: What is the current state of AI experimentation within your organization?	A) No efforts or interest expressed. B) AI is discussed but no concrete steps taken. C) One or two isolated experiments have been tried. D) At least one structured pilot project has been conducted. E) Multiple pilots or small-scale implementations are underway.
	Cultural support for IT collaboration: To what extent does your culture support collaboration around IT?	A) No internal or external collaboration related to IT. B) Limited informal collaboration exists. C) Occasional collaboration with consultants or partners. D) Ongoing collaboration through part-time support or networks. E) Strong culture of collaboration with sustained external partnerships or internal communities.

Following the assessment of all three companies across the five pillars and corresponding questions, the detailed results are presented in Table 34.

Table 34 | Detailed Results Conceptual Framework Model for AI Adoption in SMEs

Questions / Answers	Company A	Company B	Company C
Pillar 1: Question 1	D = 75	C = 50	D = 75
Pillar 1: Question 2	C = 50	B = 50	C = 50
Pillar 1: Question 3	C = 50	B = 25	B = 25
AVG Score (P1)	58.3	33.3	50
Pillar 2: Question 1	C = 50	B = 25	C = 50
Pillar 2: Question 2	B = 25	B = 25	C = 50
Pillar 2: Question 3	B = 25	B = 25	B = 25
AVG Score (P2)	33.3	25	41.7
Pillar 3: Question 1	C = 50	B = 25	C = 50
Pillar 3: Question 2	B = 25	A = 0	B = 25
Pillar 3: Question 3	C = 50	C = 50	C = 50
AVG Score (P3)	41.7	25	41.7
Pillar 4: Question 1	B = 25	A = 0	A = 0
Pillar 4: Question 2	C = 50	C = 50	C = 50
Pillar 4: Question 3	D = 75	D = 75	D = 75
AVG Scire (P4)	50	41.7	41.7
Pillar 5: Question 1	C = 50	B = 25	C = 50
Pillar 5: Question 2	B = 25	B = 25	B = 25
Pillar 5: Question 3	D = 75	D = 75	D = 75
AVG Score (P5)	50	41.7	50

After computing the average score for each pillar per company on a scale from zero to one hundred, the results are normalized to a zero-to-one range using the formulas:

$$Normalized\ Score\ (per\ pillar) = \frac{Raw\ Score}{100}$$

$$Final\ NMRS\ style\ score = \frac{1}{n}\sum_{i=1}^{n}\frac{R_i}{100}$$

- R_i = the raw pillar score for the i -th category out of a hundred
- n = number of pillars
- The scores are averaged to yield a single readiness value between zero and one.

After normalizing the results based on the proposed framework, the results are:

$$Final\ NMRS\ style\ score\ Company\ A = 0.467$$

$$Final\ NMRS\ style\ score\ Company\ B = 0.333$$

$$Final\ NMRS\ style\ score\ Company\ C = 0.450$$

Cisco AI Readiness Index [61]

The results from Cisco's Readiness Assessment are obtained through its structured self-assessment tool, which evaluates organizational preparedness across six categories: strategy, infrastructure, data, governance, talent, and culture. Each question contributes a variable number of points, reflecting its relative weight within the overall scoring framework. Upon completion, the cumulative score is interpreted according to Cisco's readiness scale, which categorizes companies into four levels of preparedness: unprepared (0–30), limited preparedness (31–60), moderately prepared (61–85), and fully prepared (86–100). According to Cisco, a minimum score of 86 is required for an organization to be considered fully capable of leveraging AI effectively within its operational processes. Table 35 presents the method of assessment.

Table 35 | Structure of Cisco Self-Assessment

Category	Question	Possible Answers
Strategy	Do you have a strategy to deploy AI powered solutions in your organization?	○ Yes - we have a well-defined AI strategy. ○ No - we are currently in the process of developing an AI strategy. ○ No - we have not yet started to develop an AI strategy. ○ Unsure.
	Is it clear who / what team is leading the AI strategy for your company or is it being managed in a more organic and decentralized manner?	○ There is clear leadership / ownership of our organization's AI strategy. ○ More organic and decentralized.
	Do you have a process in place to measure the impact of the deployment of AI / AI-powered solutions?	○ Yes, we have a process and clearly defined metrics. ○ Yes, we have a process but are still working on actual metrics. ○ No, we don't have a process or metrics, but we are likely to have this in the next 12 month. ○ No, we don't have a process of metrics and we are unlikely to have this in the next 12 months. ○ Unsure.
	Has your company established a financial strategy to ensure sustainable funding for AI deployment initiatives?	○ Yes - A short and long-term financial strategy is in place. ○ Yes - Only a short-term financial strategy is in place. ○ No - But we are currently underway with developing a financial strategy. ○ No - We have no plans presently to develop a financial strategy. ○ Unsure.
	How is your company prioritizing budget allocation between AI deployment and other technological initiatives?	○ AI deployment is the highest priority for budget allocation, and we have been given an additional budget for it. ○ AI deployment is given equal priority alongside other technological initiatives. We have some additional funding available. ○ AI deployment is important, but we will have to cut spending across other technical initiatives to fund it. ○ AI deployment is important but depends on other technical initiatives to be in place first. ○ Unsure.
Infrastructure	How would you rate your organization's current IT infrastructure in terms of scalability and flexibility to accommodate the evolving computational needs of AI projects?	○ Fully adaptable: can instantly accommodate any AI computational needs. ○ Highly scalable: designed with growth and future AI demands in mind. ○ Moderately scalable: can handle current projects but need enhancements for more complex applications. ○ Limited scalability: might need significant updates for large AI projects. ○ Not scalable at all.
	Does your organization have dedicated GPU resources available	○ Robust GPU infrastructure available for current and future AI workloads. ○ Just enough GPU resources to cater to ongoing projects.

	and integrated for processing of AI workloads?	○ Limited GPU resources for experimental purposes only. ○ No, we don’t have dedicated GPU resources available currently.
	How efficiently can your organization allocate compute resources for AI tasks based on their demand?	○ Our systems are mostly automated and efficiently allocate resources based on AI demand. ○ We have some automated resource allocation processes, but manual intervention is often required. ○ Resource allocation for AI tasks is done manually and might not be optimal. ○ We do not have a structured approach to resource allocation for AI.
	How would you assess your current data center's network performance in terms of latency and throughput, especially for AI workloads?	○ Optimal: minimal issues and tailored for the most demanding AI workloads. ○ Moderately optimal: rare hiccups with current workload but will need improvement to cater to future demand. ○ Sub optimal: we have occasional latency issues, especially with large AI workloads. ○ Not optimal: we experience frequent issues and bottlenecks. ○ Not scalable: significant upgrades are required for large AI projects.
	As your AI projects grow in complexity and data volume, how prepared is your network to adapt to these accordingly?	○ Fully flexible and adaptable: can accommodate any scale of AI projects instantly. ○ Highly scalable: designed with significant AI growth in mind. ○ Adequately scalable: might need periodic updates. ○ Somewhat scalable: potential bottlenecks for very large AI projects. ○ Not scalable: significant upgrades are required for large AI projects
	How seamlessly is your network infrastructure integrated with your AI systems to facilitate efficient data flow and processing?	○ High-level integration ensuring efficient data flow for most AI tasks, ensuring seamless operations across all AI projects. ○ Moderate integration: we've optimized major pathways but still have occasional hiccups. ○ Some basic integrations but often require manual adjustments. ○ No integration: our network and AI systems operate mostly in silos.
	How would you assess your organization's awareness and understanding of cybersecurity threats specific to AI and ML systems?	○ High awareness: have a comprehensive understanding and / or regularly update our security protocols based on new threats. ○ Moderate awareness: aware and have taken preliminary precautions. ○ Limited awareness: have some basic understanding but no specific measures in place. ○ Unaware of security threats specific to AI workloads.
	How does your organization ensure the protection of data utilized in AI models, especially during transit and at rest?	○ End-to-end encryption with regular checks and security audits, continuous monitoring and instant threat response. ○ Advanced encryption measures in place but may lack regular audits. ○ Basic encryption measures in place. ○ No specific encryption or protection measures.
	How equipped is your organization to detect and prevent unauthorized tampering or adversarial attacks on your AI models?	○ Fully equipped: have proactive monitoring and tamper detection with timely counter measures. ○ Moderately equipped: have protective measures in place but lack real-time monitoring. ○ Somewhat equipped: we are aware of the risks and have basics sorted but lack robust measures. ○ Not equipped: have not considered the cybersecurity aspect of AI workloads.
	How does your organization manage access control to AI systems and datasets?	○ Dynamic and granular access controls that adjust based on project needs and security levels, with real-time monitoring. ○ Advanced role-based access controls with periodic audits. ○ Basic role-based access in place but may lack regular updates. ○ Access is largely open and not specifically restricted.
	How ready is your company to deploy AI from a power consumption perspective?	○ Highly prepared: we have dedicated infrastructure in place to optimize power consumption in AI deployment. ○ Somewhat prepared: some measures in place to address power consumption concerns in AI deployment. ○ Not prepared: no specific measures or considerations for power consumption in AI deployment. ○ Unsure.
Data	How centralized is your organization's in-house data, facilitating easy access for AI initiatives?	○ Fully centralized: data is consistently managed and readily accessible organization wide. ○ Moderately centralized: majority of data is in unified databases, but some silos remain. ○ Partially fragmented: some centralized databases, but many department-specific silos exist. ○ Highly fragmented: data is scattered across different silos.

	To what extent is your in-house data preprocessed, cleaned, and ready for AI projects?	○ Consistently preprocessed: our data strategy ensures data is always AI-ready. ○ Mostly preprocessed: most of our data is primed for AI use. ○ Occasionally preprocessed: some datasets are AI-ready, but many require additional work. ○ Rarely preprocessed: significant time is needed to clean and organize data for AI.
	How would you describe the procedures and protocols in place for AI teams to access and use in-house data?	○ Facilitative: procedures actively promote efficient data access for AI. ○ Balanced: while there are protocols, they don't overly impede access. ○ Somewhat restrictive: procedures exist but are not streamlined so there can be occasional issues. ○ Restrictive: cumbersome protocols hinder timely access.
	How well-integrated are your analytics tools with the data sources and AI platforms used within your organization?	○ Fully integrated: almost all tools have direct, automated interactions with data sources and operate in complete harmony. ○ Moderately integrated: most tools connect seamlessly with our main data sources. ○ Somewhat integrated: some tools interface directly with data sources, but many require manual bridging. ○ Not integrated: manual processes dominate tool-data interactions.
	How would you rate the sophistication of your analytics tools in terms of handling complex AI-related data sets?	○ Excellent: majority of our tools are AI-optimized and cater to advanced tasks. ○ Good: a balance of general-purpose and AI-specific analytics tools. ○ Fair: some tools are AI-enhanced, but there's significant reliance on general tools. ○ Basic: tools are more general-purpose and don't cater specifically to AI.
	How adaptable and scalable are your analytics tools to cater to evolving AI project needs?	○ Highly adaptable: tools are frequently updated and scaled based on project demands and can be rapidly tailored to any AI analytics demand. ○ Moderately adaptable: tools cater to most AI projects, with occasional need for third-party solutions. ○ Somewhat adaptable: tools can handle current tasks but might struggle with larger, more complex projects. ○ Not adaptable: tools often lag behind project requirements.
	How would you describe the proficiency level of your staff in leveraging these analytics tools for AI projects?	○ Proficient: staff are adept at leveraging tool capabilities to their fullest. ○ Moderate: most staff can handle regular AI analytics tasks efficiently. ○ Intermediate: staff can use tools but often need guidance for advanced functions related to AI. ○ Beginner: significant training is required.
	What level of quality checks and processes do you have in place to check the quality and reliability of the external data used for AI training?	○ Advanced: external data undergoes rigorous quality checks and peer reviews. ○ Intermediate: we have a systematic process for any external data we incorporate. ○ Basic: we do some manual checks. ○ We have no systematic processes.
	How effectively does your organization track the origins and lineage of data used in your AI models?	○ Most of our AI projects have detailed data lineage tracking incorporating end-to-end data traceability, ensuring complete transparency. ○ We have a structured system for tracking data origins, but it's not integrated with all AI projects. ○ We have basic tracking but lack comprehensive lineage details. ○ We do not actively track data origins.
	How does your organization ensure and verify the accuracy of the data being used in AI models?	○ We have a continuous data accuracy validation system integrated with real-time corrections. ○ We have dedicated teams that periodically verify data accuracy. ○ We do occasional checks but lack a systematic verification process. ○ We rely on external data providers without internal verification.
Governance	What is the level of awareness across your organization regarding potential biases and fairness in data sets used for AI?	○ High awareness: regular training sessions and active discussions around biases. ○ Moderate awareness: occasional training or awareness programs in place. ○ Limited awareness: sporadic discussions but no formal understanding. ○ Not aware: haven't considered biases in our data.
	Does your organization have mechanisms to actively detect biases and lack of fairness in data used for AI?	○ Diversity in external data is a priority; regular checks for biases are conducted with continuous monitoring and adjustment. ○ We actively seek diverse data sources and occasionally audit for biases. ○ We try to use diverse data but don't have systematic checks in place. ○ This isn't a focus for us currently.

	How does your organization handle and rectify identified biases and lack of fairness in data?	○ Systematic process for bias and fairness correction with dedicated teams and proactive strategy for bias prevention and rectification, and ensuring fairness, ingrained in data management. ○ Biases are addressed on a project-by-project basis. ○ Acknowledge biases but lack systematic correction mechanisms. ○ No formal process for rectification.
	How transparent are the algorithms used in your AI systems in terms of their decision-making processes?	○ Highly transparent: can trace most decisions back to specific factors. ○ Moderately transparent: essential decision factors are known. ○ Limited transparency: some understanding but lacks depth. ○ Completely black box: no understanding of decision mechanisms.
	Does your organization have mechanisms to detect biases and ensure fairness in AI algorithms?	○ Regular comprehensive automated checks with continuous monitoring for algorithmic biases complemented with manual reviews. ○ Automated bias detection tools in place but not used consistently. ○ Sporadic manual reviews. ○ No mechanisms in place.
	What is the level of understanding across your organization about global data privacy standards (like GDPR, CCPA, etc.) and ensuring adherence to these in AI projects?	○ High understanding: strict adherence with regular audits and review and a proactive strategy to stay ahead of global privacy norms and regulations. ○ Moderate understanding: have protocols in place, but occasional lapses occur. ○ Basic understanding, but no systematic adherence. ○ Unaware of global privacy standards.
	How does your organization handle data anonymization to protect user privacy in AI datasets?	○ Consistent anonymization techniques across all datasets. ○ Advanced anonymization techniques for most AI datasets. ○ Basic anonymization techniques applied inconsistently. ○ No anonymization: data is used as is.
	In case of a data breach or privacy violation, how prepared is your organization to address and rectify the situation?	○ Advanced protocol: regularly reviewed with mock drills and updates, continuous monitoring and rapid response teams. ○ Structured protocol with designated teams but rarely reviewed ○ Basic protocol, but not comprehensive or tested. ○ No established protocol for breaches.
	How well-versed is your organization in data sovereignty laws and regulations across different regions/countries?	○ Detailed knowledge of varied jurisdictions with experts on board. ○ Good understanding of major regions/countries. ○ Basic awareness but lacks depth. ○ Not aware of data sovereignty laws.
	How does your organization ensure that data storage and processing align with local data sovereignty requirements?	○ Strict protocols with data mapped and stored according to local laws and sovereignty rules. ○ Advanced Protocols: regular checks to ensure compliance with major regions' sovereignty laws. ○ Basic protocols: some alignment with sovereignty laws, but not consistent. ○ No specific protocols: data is stored wherever convenient.
	How does your organization handle cross-border data transfers, ensuring they adhere to data sovereignty laws?	○ Rigorous checks ensuring every transfer aligns with local sovereignty laws. ○ Structured protocols for most cross-border transfers. ○ Aware but might have occasional lapses in adherence. ○ We don't consider sovereignty during cross-border transfers.
	How comprehensive are the AI policies and protocols in your organization overall?	○ Highly comprehensive policies. ○ Moderately comprehensive. ○ Limited. ○ We do not have any.
Talent	How well resourced is your company with the right level of in-house talent necessary for successful AI deployment?	○ Very well resourced. ○ Moderately well resourced. ○ Moderately under resourced. ○ Significantly under resourced. ○ Unsure.
	How would you describe the proficiency level of your staff in adopting and fully leveraging the AI technologies that you are deploying?	○ Proficient: staff are adept at leveraging tool capabilities to their fullest. ○ Moderate: most staff can handle regular AI related tasks efficiently. ○ Intermediate: staff can use tools but often need guidance for advanced functions. ○ Beginner: significant training is required.
	Has your company invested in training programs to upskill existing employees in AI-related competencies?	○ Yes, but we hire external vendors to train our staff. ○ Yes, we have comprehensive internal training programs. ○ No, we have not implemented training programs yet but plan to in the future. ○ Unsure.
	When it comes to talent management, has your company started to think	○ Yes, it is a core part of our AI strategy and talent planning. ○ Yes, we have thought about it, but there are no clear answers.

	about ‘accessibility’ of AI technologies for employees who are differently abled?	○ Yes, we are aware but we don’t build these AI tools so we can’t control this aspect. ○ No, this is not a consideration at this time.
Culture	How urgently is your organization looking to embrace AI?	○ High urgency: the move to embrace AI is seen as highly important and urgent. ○ Moderate urgency: embracing AI is seen as important but the organization is not acting with urgency. ○ Limited urgency: embracing AI is seen as an inevitable driver of some change but not important or critical. ○ No urgency: there is no discussion or momentum around embracing AI within the organization.
	How receptive is your Board to embracing the changes brought about by AI?	○ High receptiveness: widespread acceptance and willingness to adopt. ○ Moderate receptiveness: general acceptance and willingness to adopt. ○ Limited receptiveness: only limited teams / stakeholders accepting and willing to adopt. ○ Not receptive: resistant to change and will struggle to adapt. ○ Unsure: I don’t know.
	How receptive is your Leadership Team to embracing the changes brought about by AI?	○ High receptiveness: widespread acceptance and willingness to adopt. ○ Moderate receptiveness: general acceptance and willingness to adopt. ○ Limited receptiveness: only limited teams / stakeholders accepting and willing to adopt. ○ Not receptive: resistant to change and will struggle to adapt. ○ Unsure: I don’t know.
	How receptive is your Middle Management to embracing the changes brought about by AI?	○ High receptiveness: widespread acceptance and willingness to adopt. ○ Moderate receptiveness: general acceptance and willingness to adopt. ○ Limited receptiveness: only limited teams / stakeholders accepting and willing to adopt. ○ Not receptive: resistant to change and will struggle to adapt. ○ Unsure: I don’t know.
	How receptive is your Employees to embracing the changes brought about by AI?	○ High receptiveness: widespread acceptance and willingness to adopt. ○ Moderate receptiveness: general acceptance and willingness to adopt. ○ Limited receptiveness: only limited teams / stakeholders accepting and willing to adopt. ○ Not receptive: resistant to change and will struggle to adapt. ○ Unsure: I don’t know.
	Do you have a change management plan in place to address the changes brought about by deploying AI technologies?	○ Yes. ○ No.
	How would you assess the quality and depth of the change management plan?	○ Comprehensive: have thought through every aspect. ○ In progress: we have some areas fully covered; others are under review. ○ Draft: just started developing.

Upon completion of the Cisco self-assessment tool, the resulting readiness scores for the three SMEs and their normalized values are as follows:

$$Cisco\ Self - Assessment\ Tool\ Company\ A = 33pts.$$

$$Cisco\ Self - Assessment\ Tool\ Company\ B = 23pts.$$

$$Cisco\ Self - Assessment\ Tool\ Company\ C = 29pts.$$

$$NMRS\ style\ score\ Company\ A = 0.33$$

$$NMRS\ style\ score\ Company\ B = 0.23$$

$$NMRS\ style\ score\ Company\ B = 0.29$$

AI Readiness in Malaysian SMEs Framework [58]

The Framework for Readiness in Malaysian SMEs structures its evaluation around three core dimensions: People, Process, and Technology. Each dimension is represented by two key concepts identified by the author as most critical to that area. Since the original framework does not offer a direct method for quantifying readiness, this study develops assessment questions that reflect the framework's conceptual foundations while remaining consistent with its intent. Similarly to previous assessments, each question includes four predefined response options: Very Low Readiness, Low Readiness, Moderate Readiness, and High Readiness. These options are assigned numerical values from one to four, which are then used to calculate and normalize overall readiness scores. Table 36 presents the method of assessment.

Table 36 | Structure of Assessment for the AI Readiness in Malaysian SMEs Framework

Dimension	Concept / Question	Possible Answers
People	**Skilled Human Resources**: To what extent does your organization have internal employees who understand, implement, or manage AI-related systems (e.g., data analytics, ML tools, automation workflows)?	○ Very Low Readiness. ○ Low Readiness. ○ Moderate Readiness. ○ High Readiness.
	User Experience: How prepared are your employees to interact with AI tools in their daily work through user-friendly interfaces or training?	○ Very Low Readiness. ○ Low Readiness. ○ Moderate Readiness. ○ High Readiness.
Process	**Opportunities in the Value Chain**: Has your organization identified processes or areas (e.g., forecasting, inventory, routing) where AI could improve efficiency, reduce cost, or support decision-making?	○ Very Low Readiness. ○ Low Readiness. ○ Moderate Readiness. ○ High Readiness.
	Change Management: How prepared is your organization to manage change related to AI implementation, including staff adaptation, communication, and training?	○ Very Low Readiness. ○ Low Readiness. ○ Moderate Readiness. ○ High Readiness.
Technology	**Readiness of Devices and Infrastructure**: Do you have access to reliable digital infrastructure (internet, computing resources, hardware, software) that can support AI adoption?	○ Very Low Readiness. ○ Low Readiness. ○ Moderate Readiness. ○ High Readiness.
	Integration with IoT and IoE: How well can your existing systems interact with IoT devices or other data sources that would support predictive analytics, automation, or monitoring via AI?	○ Very Low Readiness. ○ Low Readiness. ○ Moderate Readiness. ○ High Readiness.

After answering the questions, the detailed results for the assessment are presented in Table 37.

Table 37 | Detailed Results AI Readiness in Malaysian SMEs Framework

Questions / Answers	Company A	Company B	Company C
Dimension 1: Q1	B = 2pts.	A = 1pt.	A = 1pt.
Dimension 1: Q2	B = 2pts.	A = 1pt.	B = 2pts.
Dimension 2: Q1	B = 2pts.	B = 2pts.	C = 3pts.
Dimension 2: Q2	B = 2pts.	A = 1pt.	B = 2pts.
Dimension 3: Q1	C = 3pts.	C = 3pts.	C = 3pts.
Dimension 3: Q2	C = 3pts.	B = 2pts.	B = 2pts.
AVG Score (P)	2.33	1.67	2.17

Following the calculation of average values to simulate a composite readiness index, the results are normalized using min–max normalization, based on the scale parameters defined within the original framework.

$$Normalized\ Score = \frac{Raw\ Score - 1}{4 - 1} = \frac{Raw\ Score - 1}{3}$$

The normalization formula maps the original values, ranging from one to four, onto a scale from zero to one using the transformation: 1 → 0, 2 → 0.33, 3 → 0.67, and 4 → 1.0. Following this conversion to a normalized readiness index, the resulting scores are as follows:

$$Normalized\ Score\ Company\ A = \frac{2.33 - 1}{3} = 0.443$$

$$Normalized\ Score\ Company\ B = \frac{1.67 - 1}{3} = 0.223$$

$$Normalized\ Score\ Company\ C = \frac{2.17 - 1}{3} = 0.39$$

Organizational Readiness Framework [65]

The Organizational Readiness Framework identifies six key dimensions of readiness that are essential for organizational preparation for AI adoption. These include resource readiness, cultural readiness, strategic readiness, IT readiness, partnership readiness, and cognitive readiness. Each dimension is further defined by specific subcomponents that collectively determine the overall maturity of the corresponding readiness aspect. Since the original framework does not provide a direct method of assessment, this study develops targeted questions that reflect both the primary and supporting elements while remaining aligned with the author's intended focus by targeting a question at each subcomponent. Each question presents four response options in increasing order of maturity: Not at all, To a limited extent, Moderately, and Fully. These responses are assigned numerical values from one to four, respectively. Table 38 presents the method of assessment.

Table 38 | Structure for Assessment of Organizational Readiness Framework

Dimension	Subcomponent Questions	Possible Answers
Resource Readiness	Does your organization have processes in place to ensure data quality and governance for AI-related operations?	○ Not at all. ○ To a limited extent. ○ Moderately. ○ Fully.
	Have financial resources been explicitly allocated for AI adoption efforts?	
	Are there structured change management practices to help employees adapt to AI-driven changes?	
Cultural Readiness	Are your organization's decision-making mechanisms compatible with AI-supported processes, such as automated recommendations or predictive insights?	○ Not at all. ○ To a limited extent. ○ Moderately. ○ Fully.
	Is there internal awareness or discussion of the ethical implications of AI, such as fairness, transparency, or responsibility?	
Strategic Readiness	Does your organization recognize AI as a strategic business enabler that offers measurable potential in your domain?	○ Not at all. ○ To a limited extent. ○ Moderately. ○ Fully.
	Does top management actively support AI adoption by setting goals, allocating resources, or engaging in related planning?	
IT Readiness	Can your organization create or simulate artificial data when genuine datasets are limited?	○ Not at all. ○ To a limited extent. ○ Moderately. ○ Fully.
	Do you take a full-cycle approach to digital development including stages such as validation, deployment, and monitoring?	
	Does your organization upgrade its software / hardware at least annually to benefit from technological advances?	
	Is your IT infrastructure designed to support integration with AI tools and accommodate data-intensive training requirements?	

Partnership Readiness	When planning new technology advancements, does your organization consider how customers or stakeholders might positively respond to these technologies?	○ Not at all. ○ To a limited extent. ○ Moderately. ○ Fully.
	Does your organization have the capability to explain to users how AI / ML models work and what their output means?	
Cognitive Readiness	Are employees in your organization generally aware of what AI is and what it can do in your sector?	○ Not at all. ○ To a limited extent. ○ Moderately. ○ Fully.
	Are there structured programs or efforts in place to develop employees' AI-related knowledge or skills?	

After answering the questions, the detailed results for the assessment are presented in Table 39.

Table 39 | Detailed Results Organizational Readiness Framework

Questions / Answers	Company A	Company B	Company C
Dimension 1: Q1	C = 3pts.	B = 2pts.	C = 3pts.
Dimension 1: Q2	A = 1pt.	A = 1pt.	A = 1pt.
Dimension 1: Q3	A = 1pt.	A = 1pt.	A = 1pt.
Dimension 2: Q1	D = 4pts.	D = 4pts.	D = 4pts.
Dimension 2: Q2	B = 2pts.	A = 1pt.	A = 1pt.
Dimension 3: Q1	C = 3pts.	B = 2pts.	C = 3pts.
Dimension 3: Q2	C = 3pts.	B = 2pts.	C = 3pts.
Dimension 4: Q1	A = 1pt.	A = 1pt.	A = 1pt.
Dimension 4: Q2	B = 2pts.	B = 2pts.	B = 2pts.
Dimension 4: Q3	A = 1pt.	A = 1pt.	A = 1pt.
Dimension 4: Q4	C = 3pts.	B = 2pts.	B = 2pts.
Dimension 5: Q1	C = 3pts.	A = 1pt.	C = 3pts.
Dimension 5: Q2	B = 2pts.	A = 1pt.	B = 2pts.
Dimension 6: Q1	B = 2pts.	B = 2pts.	B = 2pts.
Dimension 6: Q2	A = 1pt.	A = 1pt.	A = 1pt.
AVG Score (P)	2.133	1.6	2

Following the calculation of average values to simulate a composite readiness index, the results are normalized using min–max normalization, based on the scale parameters defined within the original framework.

$$Normalized\ Score = \frac{Raw\ Score - 1}{4 - 1} = \frac{Raw\ Score - 1}{3}$$

The normalization formula maps the original values, ranging from one to four, onto a scale from zero to one using the transformation: 1 → 0, 2 → 0.33, 3 → 0.67, and 4 → 1.0. Following this conversion to a normalized readiness index, the resulting scores are as follows:

$$Normalized\ Score\ Company\ A = \frac{2.133 - 1}{3} = 0.378$$

$$Normalized\ Score\ Company\ B = \frac{1.6 - 1}{3} = 0.2$$

$$Normalized\ Score\ Company\ C = \frac{2 - 1}{3} = 0.333$$

K) Guidance Comparison Survey Structure

Table 40 | Structure of Survey for the Evaluation and Comparison of Guidance from the Proposed Framework

<table>
<tr><th>Segment</th><th>Instruction</th><th>Question</th></tr>
<tr><td rowspan="6">Data Readiness Guidance</td><td rowspan="6">The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of Data Readiness and requires targeted improvements before being considered ready for the adoption of ML / AI.
Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness.
Please read the four statements below and respond to the following six evaluation questions. Your answers will help determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation.

Statement A:
It is essential that the company has the capability to integrate with different data sources or it is capable of sitting on top of a data platform for seamless data exchange. The data platform can be a Big Data platform or a Data Lake which probably is widely popular nowadays in an enterprise environment.

Statement B:
Reliable and continuous data collection and storage is fundamental to find patterns and train AI systems. Without data, it is very difficult for algorithms to discover the desired insights leading the company to resolve problems. Therefore, structuring and automating data collection has to be a priority for companies willing to adopt AI.

Statement C:
Generating high-quality data therefore seems to be of crucial importance for the implementation of ML / AI as well as the meaningfulness of the results.

Statement D:
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 ML, 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.</td><td>Which statement provides the clearest guidance on what your company should do?</td></tr>
<tr><td>Which statement best reflects your company’s current goals or challenges?</td></tr>
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<tr><td>Please briefly explain the reason behind your selection of the most useful statement.</td></tr>
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	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.	
System & IT Maturity	The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of **System & IT Maturity** and requires targeted improvements before being considered ready for the adoption of ML / AI. Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness. Please read the four statements below and respond to the following six evaluation questions. Your answers will help determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation. **Statement A:** Organizations must invest in upgrading systems and technologies to enable AI integration, as outdated infrastructure is a major barrier to ML / AI adoption. ML / AI adoption strategies typically involve increasing investments, automating processes, and upgrading systems and technologies to remain competitive. **Statement B:** A flexible infrastructure that supports fast deployment and changing use cases is needed. **Statement C:** Modular design should allow for changes in each component without affecting the entire architecture. Deployable run times are available on cloud environments like AWS, Google, Azure, which provide lower costs and easy maintenance. **Statement D:** 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 / AI 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? ML / AI 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 provides 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 dashboard. When purchasing or renewing software contracts, the SME	Which statement provides the clearest guidance on what your company should do? Which statement best reflects your company's current goals or challenges? Which statement seems most realistic to implement in your company within the next six months? Which statement is easiest for you to understand and act on? Please rank the four statements from most useful to least useful (1–4), where 1 indicates the most useful and 4 the least useful. *Example response: 1 – B, 2 – D, 3 – A, 4 – C* Please briefly explain the reason behind your selection of the most useful statement.

	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.	
Organizational & Cultural Readiness Guidance	The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of **Organizational & Cultural Readiness** and requires targeted improvements before being considered ready for the adoption of ML / AI. Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness. Please read the four statements below and respond to the following six evaluation questions. Your answers will help determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation. **Statement A:** The implementation of sustainable HR strategies that emphasize employee development and upskilling can effectively provide the workforce with the essential skills required for the effective application of ML / AI. Sustainable human capital can minimize uncertainty, tolerate risk, and reduce resistance to innovation. **Statement B:** The first step in improving organizational readiness should be to educate and engage leadership on the potential and impact of AI / ML. Employees can be encouraged to start using these tools without any cost commitment. **Statement C:** Companies must ensure workforce competencies and trust in AI systems. They must also help their employees to acquire integrated, interdisciplinary IT skills. Explainability is a prerequisite for building trust and adoption of AI systems. **Statement D:** 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? ML / AI 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 / AI. 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.	Which statement provides the clearest guidance on what your company should do? Which statement best reflects your company's current goals or challenges? Which statement seems most realistic to implement in your company within the next six months? Which statement is easiest for you to understand and act on? Please rank the four statements from most useful to least useful (1–4), where 1 indicates the most useful and 4 the least useful. *Example response: 1 – B, 2 – D, 3 – A, 4 – C* Please briefly explain the reason behind your selection of the most useful statement.
Business Process Readiness Guidance	The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of **Business Process Readiness** and requires targeted improvements before being considered ready for the adoption of ML / AI. Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness.	Which statement provides the clearest guidance on what your company should do? Which statement best reflects your company's current goals or challenges?

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<td rowspan="4"></td>
<td rowspan="4">Please read the four statements below and respond to the following six evaluation questions. Your answers will determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation.

Statement A:
Each pilot project and process optimization with AI/ML should focus on a specific business challenge, involve a limited user group, and run alongside existing systems for comparison.

Statement B:
ML / AI solutions should only be implemented if they offer demonstrable added value and represent the best solution for a real challenge for the respective company. The focus here is on the preparatory, fundamental identification of pain points and the development of corresponding alternative solutions.

Statement C:
The decision for a selected process to be optimized with ML / AI should be prioritized accordingly. Each case must meet three conditions: available historical data, measurable outcomes, and implementation feasibility.

Statement D:
It is advised that logistics SMEs transition from intuition-based 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 (e.g., delivery performance, order cycle times, sales growth, 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 ML applications, which rely on reliable feedback and visibility into historical performance. Without structured visibility, any ML / AI 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 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.</td>
<td>Which statement seems most realistic to implement in your company within the next six months?</td>
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<td rowspan="3">Strategic Alignment</td>
<td rowspan="3">The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of Strategic Alignment and requires targeted improvements before being considered ready for the adoption of ML / AI.
Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness.
Please read the four statements below and respond to the following six evaluation questions. Your answers will help determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation.</td>
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	Statement A: The strategic integration of ethical frameworks for AI / ML is necessary to support its practical and responsible use within small businesses. Strategic decisions should ensure alignment between operational deployment and value-driven principles. **Statement B:** With regards to strategy, important activities that should be addressed by strategic leadership, are direction setting, translation of strategy into action, aligning the organization and the people with the developed strategy, development of strategic capabilities and determining the effective intervention points. **Statement C:** To ensure the successful integration of AI / ML into the organizational framework, it is crucial to reinforce a long-term vision and strategic alignment. This begins with periodically revisiting and reassessing the AI / ML strategy to ensure it aligns with the company's overarching business goals. **Statement D:** It is advised that logistics SMEs establish a modest, clearly delineated budget for ML activities, even if limited in scale. This budget should cover the costs of piloting a specific ML / AI 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? ML 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 (e.g., route optimization, stock level forecasting, 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.	company within the next six months? Which statement is easiest for you to understand and act on? Please rank the four statements from most useful to least useful (1–4), where 1 indicates the most useful and 4 the least useful. *Example response: 1 – B, 2 – D, 3 – A, 4 – C* Please briefly explain the reason behind your selection of the most useful statement.
Security & Regulatory Compliance	The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of **Security & Regulatory Compliance** and requires targeted improvements before being considered ready for the adoption of ML / AI. Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness. Please read the four statements below and respond to the following six evaluation questions. Your answers will help determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation. **Statement A:**	Which statement provides the clearest guidance on what your company should do? Which statement best reflects your company's current goals or challenges? Which statement seems most realistic to implement in your company within the next six months?

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<tr><td rowspan="3"></td><td rowspan="3">An initial AI / ML ethics and governance policy should be developed, as well as data privacy and usage policies and task-specific AI / ML policies. Policy formulation at early stages plays a critical role in ensuring ethical, secure, and effective use of discriminative models.

Statement B:
Cybersecurity plays an essential role in ensuring that AI systems are resilient against malicious attempts to alter their use, behavior, performance, or security properties. Cyberattacks may target specific elements like training data or models via adversarial attacks or membership inference.

Statement C:
Security testing, vulnerability analysis and risk management should be embedded throughout the company's systems to mitigate potential misuse or attacks.

Statement D:
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 ML / AI 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 simple table listing systems, users, access rights, and 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 (e.g., 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 prioritize 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 organizational roles shift or tools are added.</td><td>Which statement is easiest for you to understand and act on?</td></tr>
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Example response: 1 – B, 2 – D, 3 – A, 4 – C</td></tr>
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<tr><td rowspan="5">External Dependencies & Ecosystem Readiness</td><td rowspan="5">The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of External Dependencies & Ecosystem Readiness and requires targeted improvements before being considered ready for the adoption of ML / AI.
Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness.
Please read the four statements below and respond to the following six evaluation questions. Your answers will help determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation.

Statement A:
Collaborative AI activities with external partners and universities enable SMEs to explore operational opportunities and achieve international growth. Furthermore, better access to customers can leverage the potential of AI. By using AI technologies, SMEs can work closely with customers and obtain first-hand feedback.

Statement B:
External dependencies must be explicitly managed and monitored, including cloud services,</td><td>Which statement provides the clearest guidance on what your company should do?</td></tr>
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<td rowspan="2"></td>
<td rowspan="2">datasets, and third-party libraries in order to input high-quality external data into existing systems and tools.

Statement C:
The burden of hiring and maintaining a dedicated AI/ML-engineering team can be outsourced from the SMEs to specialized companies.

Statement D:
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 ML / AI applications. These sources may include real-time traffic feeds, weather updates, partners / suppliers' data, 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?
ML / AI 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.</td>
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Example response: 1 – B, 2 – D, 3 – A, 4 – C</td>
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<td rowspan="6">Scalability & Long-Term Viability</td>
<td rowspan="6">The following four statements are derived from existing ML / AI Preparation Frameworks. These statements reflect practical steps that may need to be taken when a company is underperforming in the area of Scalability & Long-Term Viability and requires targeted improvements before being considered ready for the adoption of ML / AI.
Each statement describes a possible approach or action that could support a company in progressing toward ML readiness in this area. While the statements vary in focus, they are all designed to offer feasible and actionable guidance for logistics SMEs at earlier stages of readiness.
Please read the four statements below and respond to the following six evaluation questions. Your answers will help determine how clear, useful, and aligned these statements are with the needs of real-world companies preparing for ML implementation.

Statement A:
Organizations may effectively equip their human capital to adapt to the ever-changing technology landscape by making investments in ongoing learning and development initiatives, to have sustainable human capital to obtain long-term sustainability.

Statement B:
Companies must embrace a culture of continuous learning to adapt their AI / ML applications over time.

Statement C:
One of the strategic pillars is the flexibility and scalability of AI architecture to adapt over time. AI strategy should consider scalability to accommodate future data growth and emerging use cases.

Statement D:
It is advised that logistics SMEs adopt cloud-based or hybrid IT infrastructure capable of</td>
<td>Which statement provides the clearest guidance on what your company should do?</td>
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	scaling up in response to increasing computational and data-processing demands driven by ML 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 heavy processing 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.	