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reward for their service. Among others, relevant open topics to study deal with the OD engagement strategies, the reward strategy and the logistic network design and tactical management. Good examples of past research and design models are in [3–6].

This paper contributes to this topic by presenting an operations research (OR) linear programming model optimizing an urban logistic network for last-mile deliveries of B2C products using intermediate lockers as transit points and ODs as a key mobility vector next to professional carriers. The model is inspired by the real-world case of the urban area a Bologna, northern Italy, and it addresses cost and environmental targets. Starting from this purpose, Sect. 2 states the problem and describes the analytic model, Sect. 3 exemplifies its use in the historical city center of the urban area of Bologna, northern Italy, further discussing results and some managerial insights, while Sect. 4 draws conclusions and outlines feasible next steps.

2 Problem Statement and Modeling

The problem to face deals with the strategic design and tactical management of an urban logistic network for last-mile deliveries of B2C products using intermediate lockers as transit points and ODs as a key mobility vector next to professional carriers. In detail, a two stages, three tiers local logistic network is focused. The product's flow origin is from a single central depot to a set of intermediate lockers acting as temporary storage and transit points. This stage is managed by traditional carriers based on point-to-point lockers' replenishments. From the lockers the second stage of the network starts, reaching the set of the B2C clients, representing the last tier and final destination of all shipments, thanks to the use of ODs, i.e., the crowd, as unconventional carriers. ODs are assigned to clients based on their availability, feasibility limits to the quantity of products to ship and, most of all, the additional route length they have to travel, deviating from their original path, to reach the locker, picking up the product, delivering it to the client and then reaching their final destination. To compensate the ODs' effort a fee is paid based on the additional route length, while, from a network cost-based tactical management perspective, the total amount of the paid fees must be minimized. Figure 1 presents a schematic of the urban logistic network focused by the proposed model.

Inspired by practical experience and following the literature [3–5], the problem modeling lies on the following set of assumptions:

- Stage 1 is managed by traditional carriers grouping products to deliver to the same locker and reaching it with point-to-point round trips starting and ending at the single central depot
- Stage 2 is managed by ODs starting from the lockers. ODs serve clients one per trip, but they are allowed to do more trips. Limitations on the shipped quantity, the total number of trips and the maximum deviation from the OD original route exist
- The model is both strategic and tactical: lockers' selection, i.e., location problem, and client assignment, i.e., allocation problem, are done over a single planning time window
- All entities are fully known in terms of capacity, demand and reciprocal position. The same is for the unitary usage and travel cost and emissions' data
- Stage costs and emissions are variable and function of the travelled distances

- ODs represent the crowd, and they are assumed to be high enough in terms of number, availability and position in the urban area to be able to serve all clients.

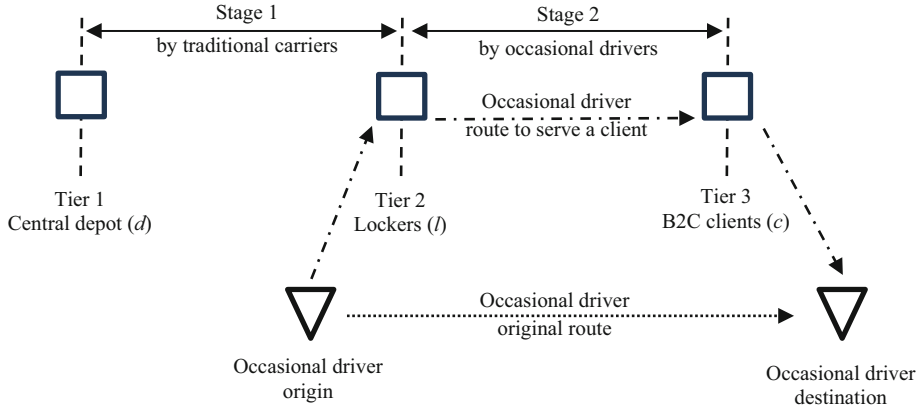


Fig. 1. Schematic of the urban logistic network with stages, tiers and the use of ODs.

The proposed problem is modelled using OR as a linear programming model with the double target of minimizing the logistic cost and environmental burden. Stage costs and emissions are considered. For the ODs a differential approach is used computing the extra costs and emissions due to the additional route length to serve the clients, via the lockers, deviating from the original OD route.

2.1 Analytic OR Model

The following notations model entities, parameters and decisional variables.

Entities

- c index for clients, i.e., destination of the second stage trips
- d index for the single central depot, i.e., origin of all the first stage trips
- l index for lockers, i.e., transit points linking the first and second stages' trips
- o index for ODs, i.e., entities making the second stage's trips

Distances

- D_{dl} one-way distance between the central depot and the locker l [km]
- D_{ld} one-way distance between the locker l and the central depot [km]
- D_{ol} distance between the OD o origin and the locker l [km]
- D_{lc} distance between the locker l and the client c [km]
- D_{co} distance between the client c and the OD o final destination [km]

- D_o distance the OD o origin and final destination [km]
 δ_{ocl} additional route length for the OD o to serve the client c via locker l [km] It follows that
 Δ^{max} upper limit to the additional route length per each OD and trip [km]

$$\delta_{ocl} = D_{ol} + D_{lc} + D_{co} - D_o \quad (1)$$

Emissions

- E^1 unitary emission, per travelled km, for the traditional carrier at the network first stage, Worldwide Harmonized Light vehicles test Procedure (WLTP) standard [7] [kg CO₂/km]
 E_o^2 unitary emission, per travelled km, for the OD o at the network second stage, WLTP standard [7] [kg CO₂/km]

Costs

- C^1 unitary cost, per travelled km, for the traditional carrier at the network first stage [€/km]
 C^2 unitary fee, per each additional travelled km, paid to the OD o at the network second stage [€/km]
 C_l^3 fix cost to use the locker l [€]

Capacities and Quantities

- K_l storage capacity of the locker l [units]
 K^1 shipping capacity of the traditional carrier vehicle [units/trip]
 K_o shipping capacity of the OD o vehicle [units/trip]
 N_o upper limit to the number of trips of the OD o during the planning period [trips]
 Q_c demand of the client c to deliver all at once [units]

Decisional Variables

- x_{ocl} 1 if OD o serves client c via locker l , 0 otherwise
 y_l 1 if locker l is used, 0 otherwise
 z_{dl} first stage round trips between the central depot d and the locker l [trips]

Two objective functions are presented to focus on alternative, but complementary, targets to achieve. Eq. (2.a, 2.b, 2.c) minimizes the total cost, C^{tot} , while Eq. (3.a, 3.b)

looks at the minimization of the environmental burden related to the two stages of the network, E^{tot} .

$$C^{tot} = \sum_l C^1 \cdot (D_{dl} + D_{ld}) \cdot z_{dl} + \quad (2.a)$$

$$+ \sum_o \sum_c \sum_l C^2 \cdot \delta_{ocl} \cdot x_{ocl} + \quad (2.b)$$

$$+ \sum_l C_l^3 \cdot y_l \quad (2.c)$$

$$E^{tot} = \sum_l E^1 \cdot (D_{dl} + D_{ld}) \cdot z_{dl} + \quad (3.a)$$

$$+ \sum_o \sum_c \sum_l E_o^2 \cdot \delta_{ocl} \cdot x_{ocl} \quad (3.b)$$

Analytically, three cost drivers are added together to costify the first stage cost of the traditional carrier (Eq. (2.a)), the total fees to engage the ODs at the second stage of the network (Eq. (2.b)), and the fix cost to use the lockers (Eq. (2.c)). Eqs. (3.a) and (3.b) quantify the environmental burden, in equivalent kg CO₂, at the first and second stage of the network, respectively. The following set of feasibility constraints complete the OR linear programming model giving consistence to the considered logistic problem.

$$\sum_o \sum_l x_{ocl} = 1 \quad \forall c \quad (4)$$

$$\sum_o \sum_c x_{ocl} \cdot Q_c \leq K^1 \cdot z_{dl} \quad \forall l \quad (5)$$

$$\sum_o \sum_c x_{ocl} \cdot Q_c \leq K_l \quad \forall l \quad (6)$$

$$x_{ocl} \cdot Q_c \leq K_o \quad \forall o, c, l \quad (7)$$

$$\sum_l \sum_c x_{ocl} \leq N_o \quad \forall o \quad (8)$$

$$x_{ocl} = 0 \quad \forall o, c, l : \delta_{ocl} > \Delta^{max} \quad (9)$$

$$x_{ocl} \leq y_l \quad \forall o, c, l \quad (10)$$

$$x_{ocl} \text{ binary} \quad \forall o, c, l \quad (11)$$

$$z_{dl} \geq 0 \text{ integer} \quad \forall l \quad (12)$$

$$y_l \text{ binary} \quad \forall l \quad (13)$$

Equation (4) forces to serve all clients by one OD via one locker, only, while Eq. (5) balances the flows at the two stages of the network. Equation (6) guarantees not to

exceed the locker capacity and, similarly, Eqs. (7), (8) and (9) set upper limits to the units per trip, the total number of trips over the planning period, and the additional route length per trip per each OD. Equation (10) links the variables x_{ocl} and y_l so that each locker is used, i.e., $y_l = 1$, if one or more clients is served by an OD that uses that locker. Finally, Eqs. (11), (12) and (13) give consistence to the decisional variables.

Globally, the model suggests the best OD to use per client, given their reciprocal positions, supporting route planning. This info is transferred, via a dedicated mobile system, supporting and providing info to the ODs about the expected effort and potential earning. The proposed model is used in the geographical context of the historical city center of the urban area of Bologna, northern Italy, to study its practical feasibility and impact. Some preliminary results are in Sect. 3.

3 Case Study and Discussion

The historical city center of the urban area of Bologna, northern Italy, is a highly populated medieval area of 5 km² and, approximately, 53,000 residents plus students, workers and daily travelers [8]. The road network is radial with a ring road limiting a limited traffic zone (LTZ) inner loop closed to commercial and private fossil fuel vehicles for long periods of time during the day, e.g., 7 am to 8 pm and, for the central areas, the LTZ is 24/7 (Fig. 2). Additionally, the roadways are often narrow and one-way with UNESCO World Heritage porticoes at their two sides (Fig. 3) further limiting the park area availability. These reasons and the position of the city in the Po Valley with limited wind flow and highly industrialized zones create a strong environmental burden of human activities with a trend, in the last decade, of +30% of CO₂, PM_{2.5} and PM₁₀ emissions due to the anthropic activities with an incidence of the logistic and transport sector far from being negligible [9].

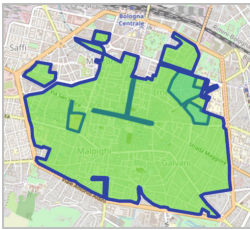


Fig. 2. Map of the historical city center of the urban area of Bologna with LTZ in green.



Fig. 3. Bologna urban roadway with UNESCO World Heritage porticoes, example.

This scenario suggests local policy makers and institutions to look for alternative last-mile delivery modes leading to the use of a lower number of vehicles. The crowd, with ODs, can contribute to decrease the commercial traffic congestion for small and frequent B2C deliveries to clients living in the city center. To this purpose a rising number of lockers has been installed by private players to manage their deliveries (Fig. 4) based on a client-to-locker paradigm.

Table 1. Case study, cost and emission savings by using ODs for the last-mile deliveries.

	Cost saving [€/day]		
OD fee	Group 1	Group 2	Group 3
2 €/km	241.4 €	238.4 €	159.3 €
4 €/km	216.8 €	210.9 €	138.7 €
6 €/km	192.3 €	183.4 €	120.6 €
	Emission saving [kg CO ₂ /day]		
OD emission	Group 1	Group 2	Group 3
0 kg CO ₂ /km	24.8 kg	24.8 kg	16.5 kg
0.08 kg CO ₂ /km	23.1 kg	22.8 kg	15.3 kg

All groups of scenarios generate a positive cost and emission saving, demonstrating the potential of using ODs for the second stage last-mile delivery. As expected, the OD fee plays a crucial role in cost saving values, even if not linear, highlighting the strong managerial insight of finding effective methods, beyond fees, to engage the crowd as ODs. Finally, results of Group 3 scenarios push managers to promote trust in this unconventional logistic paradigm so that a high number of clients ask for this service to create a critical mass sustaining its cost feasibility.

4 Conclusions and Next Steps

United Nations SDG-11 asks to make cities and human settlements inclusive, safe, resilient and sustainable and, by 2030, to provide access to safe, affordable, accessible and sustainable transport systems for all (Target 11.2), reducing the adverse per capita environmental impact of cities (Target 11.6) support positive economic, social and environmental links between urban, peri-urban and rural areas (Target 11.a) [10]. The use of the crowd to support last-mile deliveries in congested urban areas has the challenge to help reaching these ambitious targets [2, 11]. The proposed linear programming model supports the strategic design and tactical management of an urban logistic network for last-mile deliveries of business to consumer (B2C) products using intermediate lockers and occasional drivers (ODs) next to professional carriers. Next steps to overcome the current limitations are from theory to practice. The inclusion of time windows and hybrid configurations mixing professional and ODs at the same network stage are welcomed together with multi-objective policies, legal frameworks, and tools to promote this logistic solution in a wider set of urban areas.

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Warehousing, Intralogistics and Material Handling



Application of Digital Technologies in Warehouse

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Abstract. This study investigates the role of integrated digital technologies and structured, multi-layered decision-making in enhancing warehouse operations and productivity. By comparing two warehouses with different levels of technological adoption—focusing on Shuttle-Based Storage and Retrieval Systems (SBS/RS), Supervisory Control and Data Acquisition (SCADA), Warehouse Management Systems (WMS), Track-Pod, and the Trevio Warehouse platform—the research examines impacts on workflows, labor productivity, and process stability. A key focus is how strategic, tactical, and operational decision-making layers interact to support effective technology adoption. Using a two-stage methodology—qualitative case study analysis and quantitative factorial evaluation—the study provides a comprehensive assessment of technology impacts. Results show that warehouses using integrated digital technologies with data-driven, multi-level decision-making achieve significantly greater labor productivity, operational stability, and scalability. These findings underscore the importance of aligning technological investments with decision frameworks to maintain long-term competitiveness in complex logistics environments.

Keywords: logistics sector · decision making · process management · digital technologies · competitiveness

1 Introduction

Over the past decade, the logistics sector has been transformed by rapid technological advancements and rising demands for efficiency, adaptability, and resilience [1, 2]. Warehouse automation technologies—such as Warehouse Management Systems (WMS), robotic shuttle storage, real-time temperature monitoring, and digital scheduling—have become key enablers, especially in complex environments like cold storage logistics [3, 4]. These innovations enhance labor productivity, transparency, and resource utilization, but successful adoption depends equally on structured decision-making and strategic supplier collaboration [5].

However, despite extensive research on warehouse automation and decision-making, a clear gap remains in understanding how multi-layered, integrated decision-making frameworks interact with technology adoption in logistics. While prior studies examine operational efficiency or automation separately, few have investigated how strategic, tactical, and operational decision layers coordinate to support effective technology implementation.

Logistics decision-making has evolved from deterministic models to integrated, data-driven, AI-enhanced systems spanning strategic, tactical, and operational layers [2, 6, 7]. Operational decisions focus on real-time responsiveness [8], tactical decisions align medium-term planning with service goals and strategic decisions guide long-term investments for competitive advantage [9]. Integrating these layers via digital twins, IoT networks, and real-time analytics supports agility and resilience amid growing complexity [8]. Yet, empirical evidence on the joint effect of multi-layer decision-making and automation adoption—particularly in cold storage environments—is limited.

This study addresses this gap by examining how coordinated decision-making frameworks drive effective automation implementation and enhance logistics performance.

Considering these challenges, this study seeks to answer the following central research question: ***How can structured, multi-layered decision-making processes enhance the successful adoption and operational performance of warehouse automation technologies, particularly in cold storage logistics environments?***

The novelty of this study lies in its combined focus on multi-layer decision-making and empirical productivity assessment within cold storage logistics. Unlike prior descriptive studies, this research integrates qualitative insights on decision processes with quantitative evaluation of labor productivity across warehouses with differing technology levels. The study thus provides new evidence on how strategic, tactical, and operational decisions jointly influence automation outcomes, offering both theoretical contributions to decision-making frameworks and practical guidance for logistics managers.

This study advances the theory and practice of integrated decision-making in warehouse automation, particularly within cold storage logistics, offering new insights into how these elements jointly contribute to improved operational efficiency and resilience.

The article is structured as follows: Sect. 2 reviews the relevant literature on decision-making frameworks and digital technology adoption in logistics. Section 3 outlines the research methodology, which combines qualitative case study analysis with quantitative factorial statistical evaluation. Section 4 presents and discusses the findings. Finally, Sect. 5 concludes the study, highlighting key insights and directions for future research.

2 Literature Review

In the contemporary logistics landscape, decision-making functions as a central pillar of organizational adaptability, efficiency, and resilience. Accelerated by global trade expansion and the digitalization of supply chains, the pressure to make informed and timely decisions has led to a paradigmatic shift: from classical deterministic models to data-driven, algorithm-supported, and AI-enhanced decision systems [1, 2]. This section synthesizes the extant literature on logistics decision-making, offering a structured analysis across operational, tactical, strategic, and integrated layers of decision-making. The aim is not only to catalogue methods but to illuminate interdependencies, recent technological augmentations, and emerging research trajectories.

While foundational works provide a taxonomy of decision types, recent studies foreground dynamic, data-centric approaches that bridge long-term strategic aims with short-term operational responsiveness [6]. Increasingly, logistics decisions are mediated by real-time analytics, simulation-based planning, and digital infrastructures such as

IoT, blockchain, and digital twins. Such decisions are often embedded within the implementation of digital technologies in warehouse and transportation operations, enabling adaptive control, automation, and cross-layer coordination.

2.1 Strategic Decision-Making (SDM)

Strategic Decision-Making (SDM) addresses the structural and directional choices that determine long-term logistics capabilities. These include facility location, network configuration, investment in infrastructure and technology, and sustainability transformation [6]. SDM is inherently complex and unstructured, operating under high levels of uncertainty and involving multiple stakeholders. Decisions at this level shape the backbone of logistics and are increasingly supported by prescriptive and predictive analytics. AI-based forecasting can reduce logistics costs by 15% and improve infrastructure alignment with strategic goals [10]. A persistent theme in strategic literature is the tension between efficiency and agility. Examine how companies select global logistics facility locations by balancing cost-efficiency, environmental goals, and the trend toward regionalization [11].

Strategic decisions increasingly involve evaluating and selecting digital technologies, such as warehouse automation systems, IoT-based asset tracking, or cloud-based logistics platforms, as part of long-term transformation initiatives. The decision to implement such technologies requires cross-functional alignment, capital investment assessment, and simulation of expected value across network tiers.

2.2 Tactical Decision-Making (TDM)

Tactical Decision-Making (TDM) functions as the translational mechanism between long-term strategic intent and day-to-day operational execution. It involves medium-term planning horizons—typically ranging from several weeks to several months—and focuses on balancing cost-efficiency, capacity utilization, and service performance. Core tactical functions include demand forecasting, inventory optimization, transportation mode selection, workforce scheduling, and warehouse slotting [9].

One of the central challenges in TDM is managing the trade-off between responsiveness and resource optimization. Advanced analytics—particularly machine learning models for demand sensing—enable logistics planners to refine tactical decisions in near real-time, improving order fulfillment rates and minimizing backorders [12].

In the context of inventory management, techniques such as Dynamic Safety Stock (DSS), Just-in-Time (JIT), and service-differentiated inventory strategies are increasingly being customized through AI-supported simulations. These methods allow for better alignment with customer segmentation and supply variability, thereby reducing working capital without compromising availability [13].

Warehouse capacity planning and transportation allocation represent other key TDM areas where digital solutions are playing a transformative role. For example, digital twins are now used not only in operational-level simulations but also in tactical capacity forecasting, allowing managers to simulate multiple demand scenarios and plan labor shifts or fleet deployments accordingly [8].

Moreover, optimization under uncertainty has become a defining feature of contemporary tactical models. For example, fuzzy logic control systems are successfully applied to warehouse layout optimization and vehicle load planning automatically determining optimal box placements in both storage areas and transport trunks under variable load conditions. Similarly, robust possibilistic-stochastic programming models are used for designing sustainable closed-loop logistics networks, balancing on-time delivery, cost, and environmental goals amid uncertainty. Stochastic programming, fuzzy logic, and robust optimization methods handle critical variables such as lead-time variability, labor availability, and supplier reliability [14]. Notably, tactical decisions are increasingly supported by collaborative planning platforms: these digital tools enable logistics partners to co-develop demand forecasts, synchronize replenishment schedules, and negotiate shared warehouse and transport resources—for instance, within urban logistics ecosystems. Despite these advancements, the feedback loop between tactical and operational decisions often remains underdeveloped in practice. Tactical plans may be optimized in isolation without incorporating real-time disruptions from the operational layer. Addressing this disconnect represents a key opportunity for future research on adaptive tactical decision-making frameworks, particularly those that can self-adjust based on operational anomalies.

2.3 Operational Decision-Making (ODM)

Operational Decision-Making (ODM) encompasses immediate, repetitive, and execution-critical decisions that directly influence short-term logistics performance. These include order picking, delivery scheduling, inventory tracking, and dispatching—all requiring real-time responsiveness under fluctuating demand and capacity constraints [7, 15]. ODM remains the most time-sensitive and precision-driven tier of logistics, with performance metrics often tied to service level agreements and customer satisfaction [16]. Operational effectiveness increasingly depends on automation and algorithmic optimization, particularly in contexts with constrained delivery windows and high fulfillment expectations [3]. Scholars emphasize the transformative role of technological enablers, such as warehouse management systems (WMS), radio-frequency identification (RFID), and autonomous guided vehicles (AGVs) in enhancing operational responsiveness [3].

A significant evolution in ODM is the integration of digital twins, which allow simulation of warehouse and transport operations under uncertainty, enabling planners to pre-empt bottlenecks [8]. Furthermore, IoT-enabled sensor networks facilitate predictive maintenance and resource reallocation [4], while discrete-event simulations have demonstrated value in aligning strategic interventions with operational surges [17].

Current research increasingly blends ODM with multi-criteria decision-making (MCDM) and sustainability-driven optimization frameworks [7]. For instance, reinforcement learning agents can be used to optimize last-mile routing under stochastic conditions [18]. This study shows that big data-driven decision support systems (DSS) significantly improve disruption recovery by facilitating anticipatory responses [19].

Importantly, propose ODM models explicitly designed to enhance logistic resilience—an increasingly urgent research area amid growing system complexity and distribution risks, where real-time adaptability has become essential for survival [20].

2.4 Integrated Decision-Making (IDM)

As logistics systems grow in complexity and interdependence, the limitations of siloed decision-making become increasingly evident. Integrated Decision-Making (IDM) represents a holistic approach that seeks to synchronize strategic, tactical, and operational decision layers through shared data infrastructure, unified performance indicators, and intelligent control systems.

The theoretical foundation for IDM draws from systems thinking and cyber-physical systems theory, where decision-making is viewed not as a hierarchical cascade but as a feedback-driven, multi-agent process. In this paradigm, information flows bidirectionally: operational data inform tactical revisions, and strategic directives shape algorithmic rules for operational actions [21].

Technologically, IDM is increasingly supported by real-time analytics platforms, cloud-based DSS, and interoperable data standards that allow vertical and horizontal integration. For instance, digital supply chain control towers provide end-to-end visibility, enabling managers to monitor KPIs across tiers and trigger automated decision rules based on threshold deviation [8] highlight the role of such platforms in aligning short-term performance with long-term objectives by continuously learning from historical patterns and contextual variables.

Blockchain technology offers another enabling layer by ensuring secure, immutable, and transparent information exchange across organizational boundaries. Blockchain technology enhances Inter-Organizational Data Management (IDM) by building trust in collaborative environments, particularly within multi-party logistics systems [22]. When combined with IoT sensors, it allows real-time verification of asset conditions, facilitating synchronized decisions between transport, warehousing, and inventory control.

Emerging research also explores multi-agent systems (MAS), where autonomous agents—representing strategic, tactical, and operational decision units—interact and negotiate within predefined constraints. These agents may be driven by reinforcement learning, fuzzy rules, or genetic algorithms and can adapt to both internal performance shifts and external disruptions [23]. This decentralized yet coordinated approach allows for dynamic reconfiguration of logistics activities without central command dependency.

Conceptually, integrated decision-making aligns with the vision of a cognitively autonomous logistics ecosystem, in which human and artificial agents collaborate in real time, informed by shared situational awareness and common goals. Yet, significant implementation barriers remain. These include data silos, organizational misalignment, lack of interoperability, and insufficient explainability of AI-based decisions, which hinder trust and accountability across decision layers [2]. Among these, cultural barriers are often the most critical, affecting employee acceptance of new technologies, cross-functional collaboration, and adherence to standardized processes. Overcoming such barriers requires targeted change management strategies and organizational alignment to ensure that both technological and human factors are addressed effectively.

This perspective is supported by recent studies highlighting the importance of organizational culture in AI adoption [29].

Despite the extensive literature on decision-making layers and warehouse automation, several critical gaps remain. First, most studies address strategic, tactical, or operational layers separately, providing limited understanding of how multi-layer coordination affects the successful adoption of digital technologies, particularly in cold storage logistics. Second, while numerous empirical studies report productivity improvements from automation [3, 4], few link these outcomes explicitly to structured decision-making across all layers. Third, patterns, contradictions, and the conditional effects of technology adoption depending on organizational and cultural contexts are rarely examined.

This gap is significant: without understanding the interplay between decision layers, logistics organizations risk suboptimal implementation of automation technologies, inefficiencies, and missed strategic opportunities. This study addresses these gaps by integrating qualitative insights on decision-making processes with quantitative productivity assessment, providing empirical evidence on how strategic, tactical, and operational decisions collectively influence automation outcomes. Thus, the study contributes both theoretically—by extending integrated decision-making frameworks—and practically—by offering actionable guidance for logistics managers in cold storage environments.

3 Methodology

This study adopts a mixed-methods research approach, which combines qualitative case study analysis with quantitative factorial statistical evaluation to examine the impact of digital technology adoption in warehouse operations. The qualitative component is explicitly grounded in a structured, multi-layered decision-making framework informed by Rogers' Diffusion of Innovations model and Cooper's Stage-Gate process, providing a theoretical lens to interpret operational decisions. The qualitative component provides an in-depth exploration of decision-making processes and technology implementation practices within a real-world logistics context. This theoretical framing clarifies which aspects of the process are derived from prior literature and conceptual models. In parallel, the quantitative analysis evaluates labor productivity data across two contrasting warehouse environments, one with high technological integration and the other operating with predominantly manual processes during the period (2020–2024). The quantitative component follows a factorial evaluation framework. The first factor is the level of technological integration (high vs. low), and the second factor is the operational shift (day vs. night). Warehouses are treated as blocks to account for site-specific characteristics, while data collection across multiple years ensures robustness against seasonality and demand fluctuations. The primary response variable is labor productivity, measured as orders processed per labor hour, complemented by secondary indicators such as the error rate (percentage of incorrect picks) and the average throughput time (order processing duration). Data were analyzed using descriptive and comparative statistical methods, focusing on differences in group means, variation patterns, and temporal trends across factor levels. The factorial design allows linking empirical results back to the theoretical framework, illustrating how decision-making stages and supplier selection influence observable productivity outcomes. The dataset utilized for this study was extracted from the company's Axapta database, ensuring comprehensive and consistent operational records. Although the analysis relies on descriptive and comparative statistics rather than

formal inferential modeling, the factorial design ensures systematic evaluation across predefined factor levels. This approach provides empirical validation of the conceptual model and demonstrates the practical relevance of the decision-making framework.

This dual approach enables both contextual understanding and empirical validation of the effects of automation and digital platforms on warehouse performance.

3.1 Decision-Making Process of Technology Application Process

The implementation of new technologies follows a structured, multi-phase decision-making framework. This process is shaped by the complexity of automation solutions and their anticipated return on investment (ROI), both of which are essential determinants in the evaluation and deployment of technological systems. Applications are typically classified based on their automation level: semi-automated systems, which involve partial human intervention, and fully automated systems, which function autonomously. When implementing new technologies, companies are primarily influenced by two factors: lead time flexibility and a clearly quantifiable return on investment (ROI). Organizations seeking to implement automation frequently undergo comprehensive digital transformation initiatives, which often include upgrading enterprise resource planning (ERP) systems such as Microsoft Dynamics AX (Axapta), SAP, or Equinox. This theoretical framing guides empirical observation, linking observed practices to established models of innovation adoption. However, warehouse automation is not a one-time initiative; it represents an ongoing process of improvement that requires periodic system refinements to align with dynamic operational needs [24]. A central component of the automation journey is supplier selection. In this context, suppliers are expected not merely to provide hardware, but to deliver integrated solutions. These solutions typically consist of four interconnected elements: mechanical infrastructure (e.g., metal constructions), software systems, service and maintenance, and physical installation. The supplier thus transitions from a transactional vendor to a strategic, long-term partner [25]. The entire implementation cycle—from the initial proposal to full deployment—typically spans between 18 and 24 months, although this duration can vary significantly depending on the size and complexity of the company; in larger organizations, the process often takes considerably longer. Implementation may also face cultural and organizational barriers, including resistance to change, siloed communication, and lack of trust in new technologies, which can impact adoption timelines and effectiveness. Supplier selection is guided by structured evaluation tools, such as the Kraljic matrix, which assesses candidates against multidimensional performance criteria present in Fig. 1. The combination of qualitative observations and quantitative outcomes demonstrates how the structured decision-making process and supplier evaluation influence labor productivity and operational performance in practice.

The Kraljic Matrix is a strategic procurement tool designed to optimize supplier management by segmenting purchases based on two critical dimensions: supply risk and profit impact [5]. The matrix is divided into four quadrants, or purchasing categories, each representing a distinct procurement strategy depending on the relative positioning of a product or supplier along these axes. The horizontal axis represents supply risk, ranging from low (stable supply markets with numerous vendors) to high (volatile markets, limited suppliers, or technological complexity). The vertical axis captures profit

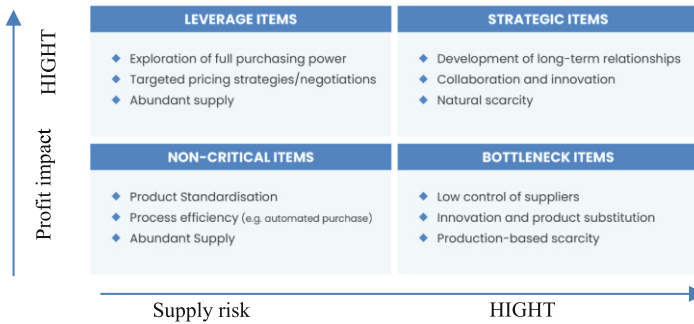


Fig. 1. Kraljic Matrix

impact, ranging from low (non-critical items with minimal cost or strategic influence) to high (products or services that significantly affect financial performance, production continuity, or value delivery). The Kraljic Matrix plays a crucial role in guiding the selection of automation solution providers. Given the complexity, capital intensity, and operational significance of these systems, such suppliers typically fall within the Strategic Items quadrant. The selection process, therefore, emphasizes risk mitigation, cross-functional alignment, and long-term value co-creation rather than short-term cost optimization.

The decision-making framework comprises eight sequential stages, conceptually aligned with Rogers’ Diffusion of Innovations model and Cooper’s Stage-Gate innovation process, both of which emphasize phased development, risk mitigation, and stakeholder alignment [26, 27]. These stages are summarized below and illustrated in Fig. 2.

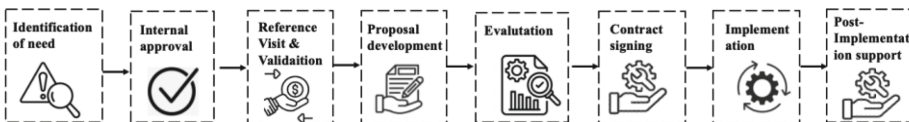


Fig. 2. Decision-Making technology implementation processes

In Stage 1, the need for automation is identified in response to various internal or external pressures, such as workforce shortages, increasing market competition, cost-reduction imperatives, and the desire to minimize human error in logistics processes, prompting organizations to consider automation as a strategic lever for operational efficiency and long-term competitiveness.

In Stage 2, internal approval for implementation is secured from senior management, enabling the allocation of strategic and financial resources, ensuring cross-functional alignment, and formalizing organizational commitment toward initiating the automation project.