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ORIGINAL PAPER

Adoption of AI-based order picking in warehouse: benefits, challenges, and critical success factors

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Abstract

This research assesses the adoption of artificial intelligence (AI)-based batch order picking in a warehouse, focusing on benefits, challenges, and critical success factors. Using customer order data and simulation, the study employs a quantitative approach, combining mathematical and statistical estimations with qualitative examinations centered on interviews with the warehouse staff, its Enterprise Resource Planning (ERP) developer, and the AI developer. The findings of this mixed-method study reveal that the AI-based order-picking system (AI-based system) has improved order-picking efficiency by reducing travel distance and time. Nevertheless, challenges hinder maximum utilization of the system. In addition, the research highlights critical success factors and other benefits of adopting the system tailored to warehouse management. Understanding the lessons learned in this research is essential for businesses seeking to adopt AI to enhance their efficiency.

Keywords Artificial intelligence · Order picking · Optimization · Warehouse · Critical success factors · Challenges · Benefits

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1 Introduction

Warehousing plays a crucial role in logistics systems, accounting for approximately 20% of a company's total logistics costs (Perotti and Colicchia 2023). Warehouse activities include: receiving, which involves unloading items from carriers, checking for quality and quantity inconsistencies, and updating inventory records; transferring and putaway, which cover the movement (and potential repackaging) of received items to storage within the warehouse; order picking, which entails fulfilling customer orders by collecting the correct quantities of the specified items; sorting, which involves grouping items based on individual customer orders; and value-added services, such as kitting and labeling (de Koster et al. 2007; Richards 2018).

Order picking is the primary activity within a warehouse (Ahmed et al. 2024; Chou et al. 2024; Grosse 2024; Saylam et al. 2024). It accounts for a significant portion of a warehouse's total operating costs, ranging from 35 to 75%. Inefficiencies in this activity can have a substantial impact on the entire supply chain (Coyle et al. 1996; de Koster et al. 2007; Richards 2018; Stević et al. 2022). Various methods and mathematical models, such as heuristic approaches and benchmarking techniques, have been employed to improve order-picking activity and reduce costs (Gu et al. 2010; Bukchin et al. 2012; Masae et al. 2020). Moreover, the literature has explored the contribution of Industry 4.0 technologies, such as the Internet of things, robotics, and automation (Poon et al. 2009; Marchet et al. 2015; Lee et al. 2018; Richards 2018; Calderon-Monge and Ribeiro-Soriano 2024; Custodio and Machado 2020; Chou et al. 2024). Among these, AI stands out as a key technology with the potential to improve warehouse management (Min 2010; Zhang et al. 2021; Sodiya et al. 2024). AI is primarily designed to understand human intelligence, enabling the creation of computer systems that replicate human behavior patterns and generate knowledge for problem-solving (Min 2010; Secundo et al. 2024). Additionally, AI has the capability to augment its observational power, identifying patterns in data that were previously undetected (Daugherty and Wilson 2018; Naeem et al. 2024).

Despite this, the targeted improvements driven by AI have often not been realized due to an inadequate understanding of how AI applications should be managed and aligned with other applications (Zhang et al. 2021; Schwaeke et al.. 2025). A report indicates that 85% of AI projects did not achieve the initially planned benefits for businesses (Rayome 2019). This outcome could be attributed to inaccurate estimations of the benefits of AI for businesses. In addition to the potential benefits, numerous practical challenges may hinder the realization of these benefits (Zhang et al. 2021). For instance, ethical concerns, privacy issues, safety and security threats, and challenges in human–robot collaboration were highlighted in a study by Javaid et al. (2022). A case study by Balzereit et al. (2023) suggests that the key challenges in order picking are developing an appropriate problem model and implementing a suitable solution algorithm. Furthermore, the readiness of warehouses to adopt AI remains a significant area that is largely unexplored (Mahroof 2019).

These statements underscore the importance of research focused on the benefits, challenges, and critical success factors that influence the readiness of businesses to adopt AI. Moreover, the exploration of use cases for AI and advanced technologies in warehouses has not been adequately studied (Mahroof 2019; Custodio and Machado 2020).

Therefore, based on the following facts and arguments: (1) the importance and high cost of the picking activity in the warehousing process (Coyle et al. 1996; de Koster et al. 2007; Richards 2018; Stević et al. 2022); (2) AI's problem-solving capabilities (Min 2010; Daugherty and Wilson 2018; Naeem et al. 2024; Secundo et al. 2024) the failure of businesses to achieve the planned benefits of AI (Rayome 2019); (4) the potential impact of research-driven identification of benefits, challenges, and critical success factors in determining the success or failure of AI initiatives (Zhang et al. 2021); and (5) the inadequate studies on AI cases in warehouses (Mahroof 2019), this paper aims to address the following research questions:

1. What are the benefits associated with the AI-based system in the order picking activity of the warehousing process?
2. What are the challenges associated with achieving the benefits of the AI-based system in the order picking activity of the warehousing process?
3. What are the critical success factors in achieving the benefits of the AI-based system in the order picking activity of the warehousing process?

The term *benefits* refer to the positive outcomes and improvements that can be achieved from using the AI-based system. *Challenges* encompass the obstacles and barriers that can hinder the successful implementation and utilization of the technology (Birkel and Hartmann 2019). *Critical success factors* are the factors that, when effectively addressed, significantly enhance the likelihood of achieving the desired improvements driven by the system (Pinto and Rouhiainen 2001, as cited in Nasir and Sahibuddin 2011). This study uses the technology-organization-environment (TOE) theory (Tornatzky et al. 1990) to contextualize the benefits, challenges, and critical success factors associated with the AI-based system in the warehouse. Furthermore, by linking these factors to the dynamic capabilities of Teece et al. (1997)–namely, *sensing, seizing, and transforming*, with a particular focus on sensing and transformation components– we aim to provide insights into how firms can effectively adopt and utilize AI-driven innovations.

In order to address the research questions, a single case study was conducted, focusing on the implementation of an AI-based system in a warehouse located in Türkiye. In this case study, an AI-based system refers to a technological system that relies on the properties of AI as its main component, together with other supplementary technologies (simulation and cloud), with the goal of enhancing the order-picking activity in the warehouse.

2 Literature review

2.1 AI in warehouse management

AI is a broad term that encompasses various technologies and applications (Helo and Hao 2022). AI can be the underlying element for other technologies, such as robots and automation (Dash et al. 2019). In essence, AI refers to machines or systems that possess intelligence comparable to or, in some cases, surpassing human cognitive abilities (Wang et al. 2023).

Past literature has shown that AI can play a significant role in improving supply chain processes, such as sales, smart connected products, operations, and service maintenance (Helo and Hao 2022). Based on a survey of 250 company executives, Davenport and Ronanki (2018) highlight the targeted benefits and challenges that are often associated with AI for businesses. These benefits are product improvement, enhanced decision making, new product development, operational optimization, increased worker freedom, expansion into new markets, acquisition and application of scarce knowledge, and reduced workforce through automation. Conversely, the challenges identified include complex integration of AI with existing systems and processes, the high cost of AI technology and required skills, limited managerial understanding of AI technologies and their functioning, limited specialized human resources, technological immaturity of AI, and overselling of AI technology in the marketplace.

The previous literature on AI in warehouses explores its applications, benefits, challenges, and critical success factors. Khan et al. (2021) focus on using robots and AI to ensure food safety. Zhang et al. (2021) emphasize the importance of integrating AI elements, such as data, algorithms, and robots with warehouse-specific systems to enhance forecasting, planning, and learning. They also highlight the evolving role of human capabilities alongside AI. Mahroof (2019) identifies benefits, such as reduced travel time and precise picking processes, while also emphasizing challenges, such as technology maintenance, system interoperability, and limitations of managerial knowledge.

In their categorization of AI, Metaxiotis et al. (2003) state that there are three types of AI (as cited in Meyer et al. 2020). The first type is *expert systems*, which utilize an extensive database on the topic to find an answer to the problem. The second type is *artificial neural networks*, which search for patterns within the available data. The third type is *autonomous agents*, which can autonomously act in a given environment.

In warehouses, AI enables automation, which is manifested in different ways, such as automated tridimensional storehouse (Zhang et al. 2021) and machine-based order picking (de Koster et al. 2007). With its pattern-finding capability, AI can help with various warehouse-related tasks, such as demand forecasting (see, for example, Zhang et al. 2021). Moreover, AI-based expert systems can contribute to the management of flexible order-picking systems (Manzini et al. 2005).

Expert systems are AI-driven computer programs that can emulate human thinking to produce an outcome that a human expert could (Olson et al. 1992, as cited in Mirčetić et al. 2016), often much faster and with fewer errors. It is a useful tool to help decision making within a domain where expertise is demanded (Turban 1995). Expert systems enable transforming knowledge into wisdom, thereby assisting the knowledge-gaining process (Shokouhyar et al. 2019). Past literature has demonstrated various applications of expert systems (Yao et al. 2010; Mirčetić et al. 2016; Patriarca et al. 2016; Leung et al. 2018). For example, expert systems can assist with decisions on defining inventory levels (Patriarca et al. 2016) or optimizing the use of forklifts in cargo loading (Mirčetić et al. 2016). The AI-based systems utilized in this paper refer to the expert system type, specifically designed for route optimization in warehouse order picking.

2.2 Order picking

Order picking activity is a critical component of the warehousing process, involving the selection and collection of the correct items in the right quantities based on customer orders (de Koster et al. 2007). There are three primary order-picking strategies: *picker to goods* where the picker retrieves the customer's order and travels through the warehouse to pick the items, either by foot using trolleys or cages, or by pallet jacks and forklift trucks using pallets; *goods to picker*, which involves storing the items in narrow aisle racking or in the automated storage and retrieval system (AS/RS) and automatically moving them to the picker's workstation, thereby reducing picker travel time; *automated picking*, which means the order picking activity is fully automated, using various advanced technologies and equipment (Richards 2018). Each of the above-mentioned strategies has its own advantages and disadvantages. Among them, picker to goods is the most commonly applied order-picking strategy (de Koster 2004; de Koster et al. 2007; Richards 2018). This strategy is also employed in the warehouse case discussed in this paper.

There are four approaches in the picker to goods strategy: cluster picking, batch picking, zone picking, and wave picking (Richards 2018). The cluster picking approach involves pickers taking on a number of customer orders together, traveling through the warehouse and picking items jointly. The picked items are immediately sorted and grouped into their respective cages or trolleys based on the composition of the orders. Batch picking also includes joint picking for different orders, but the orders are clustered and sorted after the picking is completed. With zone picking, pickers are assigned to different areas/zones in the warehouse to perform picking in their corresponding zones. In this approach, order picking can flow from one zone to the next, either simultaneously or sequentially, depending on the degree of activity and frequency of customers' orders until the picking process is completed. Finally, wave picking involves the grouping and releasing of orders at specific times throughout the day or in step with cycles of replenishment, departure of vehicles, alterations in shifts, locations and commonality of products, priorities, and requirements for value-adding services. In addition to these four approaches, there is the single order-picking approach in which the picker travels across the warehouse to fulfill one customer order at a time (Lin and Lu 1999).

Recent literature on AI-based order picking reveals significant advancements in optimizing warehouse operations through various AI-driven methods and technologies. Zarinchang et al. (2024) introduced an AI algorithm that reduced picker travel distances and improved efficiency. However, despite efficiency gains, the improvements in rack stability and safety were only moderate. Sodiya et al. (2024) emphasized the significant role of AI-driven autonomous mobile robots in enhancing inventory management and order fulfillment by optimizing routes and adapting to warehouse changes. Kalkha et al. (2024) introduced an AI algorithm that clusters and positions items with similar demand patterns, reducing order preparation time and unnecessary movements. De Assis et al. (2024) recommended further exploration of technologies, such as digital twins, to advance intelligent warehouse management. Zhao et al. (2024) proposed a goods-to-picker system combining AI and robotics to improve picking efficiency. Balzereit et al. (2023) used AI to optimize order picking by merging small orders and re-sequencing them to save time. Zhou et al. (2023) demonstrated how a batching AI algorithm could optimize order-picking schedules in smart warehouses. Cano et al. (2023) showed that a genetic algorithm outperforms ant colony optimization in picker routing, which enhances performance and speed.

3 Theoretical background

The technology-organization-environment (TOE) theory, proposed by Tornatzky et al. (1990), offers a comprehensive perspective on how firms adopt technologies. In this paper, the TOE theory is used to present the authors' views on the benefits, challenges, and critical success factors associated with the AI-based system in the order-picking activity of the warehousing process. TOE highlights three elements: technological context, organizational context, and environmental context, which impact a firm's adoption decisions (Baker 2012). Technological context encompasses all perceived sub-elements related to both new and existing technologies within the firm; organizational context refers to intra/internal aspects, such as top management support and resource availability; and environmental context includes external elements, such as partners and regulatory bodies (Zhu et al. 2006; Baker 2012).

TOE is considered a generic theory (Zhu and Kraemer 2005; Baker 2012), meaning that different sub-elements can be inserted into each of the three contexts (see, for example, Baker 2012, Table 12.1). This flexibility enables researchers to adapt the theory to different research settings and specificities. In line with this understanding, this paper utilizes the TOE theory reciprocally to explore the benefits, challenges, and critical success factors associated with AI-based systems in the order-picking activity of the warehousing process across technological, internal, and external (environmental) levels. By adopting the TOE framework, this paper takes a holistic view that extends beyond the boundaries of a single firm. It considers the broader technological setting and external actors, which can prevent certain potential benefits, challenges, and critical success factors from being missed. By utilizing TOE, the authors approach this topic by identifying the benefits, challenges, and critical success factors in the three above-mentioned contexts, thereby offering a rather more comprehensive insight into the case under focus.

Previous studies have utilized TOE to examine the benefits, challenges, and critical success factors associated with technology usage in different processes, such as procurement (e.g., Mishra et al. 2007), production (e.g., Fattouh et al. 2023), and warehousing (e.g., Mahroof 2019; Ali et al. 2023). Breaking down warehouses into processes, resources, and structures, Hassan et al. (2015) applied the TOE framework to study the adoption of information systems in warehouse management. Building on this firm-level theory, Mahroof et al. (2019) examined how a warehouse management company perceives AI adoption, focusing on technological, organizational, environmental, and perceived benefit aspects. Their study found that an AI-driven ordering system can effectively identify sales trends and automatically trigger order-picking volumes for daily distribution. Ali et al. (2024) applied the TOE framework and identified that the most influential factors driving a warehouse's readiness to transition to a smart warehouse are the operational efficiency of the technology, support from top management, employees' education, and technical expertise. This paper follows a similar path and takes the view that the rather wide-ranging foci of TOE can offer a more comprehensive analysis of the benefits, challenges, and critical success factors associated with the AI-based system for the warehouse. The benefits, challenges, and critical success factors in these three contexts are based on the pertinent literature and specifics of the case, consistent with the generic nature of this theory.

Moreover, TOE illuminates three contexts that affect a firm's mobilization of technological resources. This aligns with the resource-based view (RBV), which emphasizes the importance of resources in driving strategies and gaining a competitive advantage (Maier and Remus 2002; Soosay et al. 2016). Traditionally, RBV asserts that a firm's bundle of capabilities and resources that are valuable, rare, imperfectly imitable, and non-substitutable enable the development of a sustainable competitive advantage (Barney 1991; Amit and Schoemaker 1993). RBV suggests that a firm's strategic position and sustainable competitive advantage depend on how it manages and exploits its internal resources (Tell 2020).

Extending RBV, Teece (2007) suggested *dynamic capabilities* as a means to address the static nature of RBV, which focuses mainly on *internal* resources. Teece et al. (1997) define dynamic capability as "*the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments*" (p. 516). Teece (2019) argues that RBV falls short in emphasizing the dynamic nature of technological cycles, limiting its ability to recognize how certain firms persistently sustain their competitive advantages over time. He spotlights dynamic capabilities as a tool through which firms can mobilize the necessary resources that are previously external to them. He offers sensing, seizing, and transforming components of dynamic capabilities through which firms can import, align, and subsequently exploit these resources (Teece 2019).

Accordingly, in the context of this paper, sensing refers to forming a judgment, including comprehending benefits and challenges, on the AI-based system. Seizing centers on mobilizing the system, while transforming involves aligning the organization to the AI-based system. With regard to transforming, Teece (2019) notes that there is no one-size-fits-all alignment process because it varies according to the situation. Therefore, critical success factors highlight those elements necessary for alignment that are applicable to diverse situations.

In short, by identifying the trio of benefits, challenges, and critical success factors, this paper seeks to contribute directly to the dynamic capabilities' sensing (through benefits and challenges) and transforming (through critical factors of success) components that, in turn, affect the seizing component. Furthermore, by placing the trio into the TOE's internal, external, and technological contexts, the adoption of dynamic capabilities is further facilitated because adopters understand the contexts from which the benefits and challenges in sensing arise, and the contexts to which the critical success factors in transforming belong.

4 Methodology

This study adopts the single case study, utilizing a mixed-methods approach combining both quantitative and qualitative techniques. Specifically, the single case study focused on a warehouse in Türkiye to examine the adoption of an AI-based system. A single-case study approach was selected to investigate an AI-based solution in a specific warehouse setting, accommodating the distinctive situational nature of AI adoption (Gummesson 2017; Yin 2018). This method allows for the detailed exploration of case-specific complexities, providing insights that broader studies might overlook. Moreover, focusing on one case enhances analytical precision and relevance to the particular scenario.

Moreover, the mixed-methods approach utilized in the design of the study facilitates a comprehensive analysis of the different dimensions of new technology adoption in an organization (see Creswell and Clark 2017; Tashakkori et al. 2020). This approach allows us to capture both measurable performance outcomes of using AI-based order picking and the unmeasurable context-dependent details. Adopting advanced technologies, such as AI, in an organization is inherently complex, and this process comprises various factors that interact in diverse ways. The most challenging aspect of conducting social sciences research in such settings is that these factors are not always directly measurable, making it challenging to capture the full scope of simultaneous relationships through purely quantitative methods (İzmir 2023). Consequently, this study adopts an explanatory sequential mixed-methods design (Creswell et al. 2003) to comprehensively investigate the adoption of AI-based order picking in a warehouse in Türkiye. This design combines quantitative insights with qualitative data (see Clark 2017). Previous research has emphasized the potential of the interplay between qualitative and quantitative methods for a broader understanding of the phenomenon under focus (Ryan et al. 2011; Soltani et al. 2014).

In the first phase, quantitative data is collected and analyzed to assess the improvements in operational efficiency brought about by the AI-based order-picking system. Specifically, the focus is placed on measuring changes in travel distance and the time required for order picking before and after adopting the AI technology. Distances are recorded in meters and centimeters, while time is tracked in minutes and seconds. These two continuous variables also emerged in the qualitative phase, where they were identified under the theme of travel distance and time reduction. The quantitative analysis provided numerical data, which brought objectivity to the study's findings, demonstrating the tangible benefits of AI-based system adoption in terms of increased operational efficiency (D'Haen et al. 2023). However, quantifying these benefits alone fails to capture the full spectrum of benefits, challenges, and critical success factors identified qualitatively.

Subsequently, qualitative data is collected and analyzed following the quantitative phase to gain relevant and complementary insights. The qualitative phase involved conducting in-depth interviews and gathering open-ended survey responses from warehouse managers and employees, its ERP developer, and the AI-based system developer (Mahroof 2019). Such an approach can be an effective tool to identify important elements for the better design of order picking (Grosse et al. 2015). The qualitative data facilitated an understanding of the perceptions, attitudes, and experiences of those directly involved in the process (Mahroof 2019). Moreover, the qualitative analysis highlighted perspectives on additional benefits beyond travel distance and time reduction. In addition, the qualitative approach helped identify challenges and critical success factors that were not captured through the quantitative phase. This qualitative approach delved into aspects that are not easily quantifiable but are critical for understanding the overall impact of the AI-based system.

The mixed-method approach, which integrates qualitative and quantitative findings, can be more demanding and resource intensive task than a single-method approach but offers enhanced validity, reliability, and a more comprehensive perspective on specific aspects of the AI-based system (Abowitz and Toole 2010; Nanthagopan 2021). While quantitative data analysis provides statistical rigor, it may overlook important contextual details and fail to capture the complexity of human experiences and perspectives (Creswell 2012). Hence, the deployed mixed -methods approach aims to fulfill this lacuna (see Clark and Ivankova 2016). Such an approach ensures a thorough evaluation of the adoption process, addressing measurable outcomes (Tajima et al. 2020) and the human factors influencing these outcomes (Mahroof 2019).

4.1 Case description

The case revolved around the adoption of an AI-based system in the warehouse. The goal was to identify the benefits, challenges, and critical success factors associated with the adoption of the AI-based system in the warehouse.

With the advent of Industry 4.0, the warehousing process gains significant importance in the supply chain. According to Voss (2021), the increase in the customization of products and the potential for rapid fluctuations in demand in the Industry 4.0 era have heightened the complexity and the efforts required for activities such as picking, packing shipment, and resource management. Consequently, the warehouse's tasks expand, and resource management intensifies to improve supply chain efficiency (Voss 2021). In the context of Industry 4.0, supply chain warehousing needs to be more efficient and responsive due to the growing complexity of the activities involved. Indeed, order picking is the major activity in warehousing and represents a large portion of the warehouse's operating cost. Thus, inefficiency in this activity has a vital impact on the entire supply chain (Coyle et al. 1996; de Koster et al. 2007; Richards 2018). Therefore, investigating a system with such improvement potential, along with its corresponding challenges and critical success factors, is vital to respond to the emerging demands surrounding the warehousing process in Industry 4.0.

The case study's warehouse is located in Türkiye. Türkiye was selected for several reasons. First, Türkiye's strategic geographic location, a bridge between Europe, Asia, and the Middle East, makes it a vital hub for international trade and logistics (Özdemir 2010; Acar et al. 2015, 2020). The country's advantageous geographical location and role as a gateway to various markets necessitate the adoption of advanced technologies to optimize warehouse operations and enhance competitiveness (Saatçioğlu et al. 2009; Erol et al. 2021). Secondly, due to the growing demand for efficient and accurate order fulfillment processes, the implementation of AI technologies in warehouse operations has become crucial (Cergibozan and Tasan 2022). Moreover, the Turkish government has actively supported the digitalization of industries, including logistics, through various initiatives and incentives (Duman and Akdemir 2021).

Nevertheless, Türkiye has delivered mediocre results in transitioning to advanced technologies and Industry 4.0. (Izmen et al. 2020). Hence, investigating the benefits, challenges, and critical success factors associated with an AI-based system in a Turkish warehouse aligns well with the current status and characteristics of Türkiye's transition to advanced technologies and Industry 4.0.

The AI-based system was developed by Kairos Logic AB (hereafter Kairos), a Swedish microservices company providing dynamic order-picking intelligence to help businesses meet logistic and warehouse process needs. Kairos's AI-driven algorithms optimize warehouse and logistics resources to drive customer operations efficiently. Sienzi Lojistik Antrepo ve Dış Tic. Ltd. Şti. (hereafter Sienzi), a well-established company in the field of warehousing in Türkiye, has adopted this AI-based system, offering a wide range of services to meet customer needs (Sienzi 2023). Sienzi's warehouse covers an area of 7000 square meters, including 6,000 square meters of closed storage and 1000 square meters of open space. Its 14-m height allows a 500-pallet racking system, and there are various areas for inspection, handling, and reservation, all compliant with customs regulations. The 14 hydraulic ramps enable simultaneous operations for up to 8 trucks while smaller vehicles can be serviced in the open yard area. The company is located near the Muratbey Customs Directorate and ensures timely delivery through regular courier services. Sienzi has served 2,819,165 product entries over the past ten years. Alongside its warehousing capabilities, the company offers value-added services, such as handling, packaging, and palletizing. Sienzi has expanded its operations to include e-commerce logistics, catering to online businesses' storage and distribution needs. Furthermore, the company provides loading services for international exports. The company operates on a project basis, and during the study of AI adoption in the warehouse, the company project focused on automobile parts.

4.2 Case specificities

The warehouse uses a conventional layout structure. This layout arranges racks with parallel aisles (Oxenstierna et al. 2022). Figure 1 depicts the layout of the warehouse. Products are organized from the bottom of the shelves, grouping similar products within each column. Then, another product is placed similarly, following the same bottom-to-top arrangement. Furthermore, the figure illustrates how a warehouse lay-

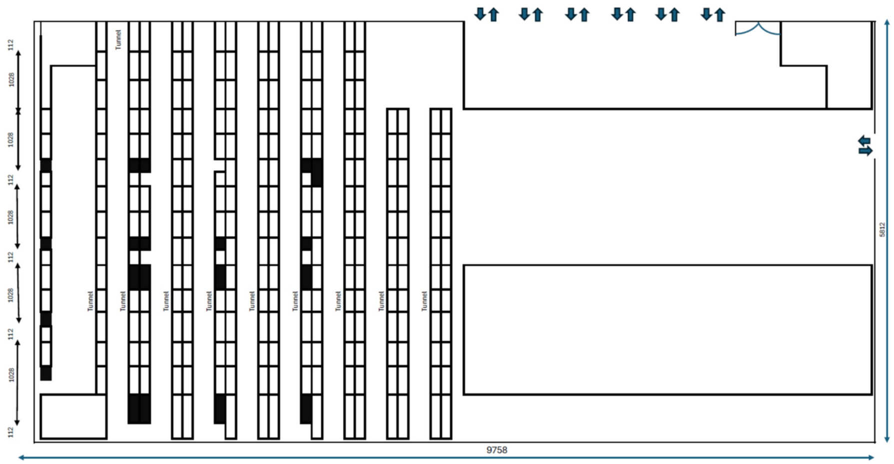

Fig. 1 The warehouse sketch

out is designed specifically for order picking. The collection point is located at the top right corner, and there is a designated tunnel that serves as the primary pathway for pickers to navigate through the aisles to pick up customer orders.

Using historical pick runs spanning a month and the warehouse's floor map, Kairos developed a digital twin simulation of the warehouse. By utilizing the cloud technology, the digital twin can then apply AI algorithms to improve order picking in Sienzi. The integration of the AI-based system with the warehouse's ERP was achieved through the establishment of an application programming interface (API). The ERP system, developed by Select Bilişim Hizmetleri AŞ (hereafter Select), one of Türkiye's well-established logistics software companies, also includes a warehouse management system (WMS) module. Based on customer order data from the ERP, the AI-based system has produced optimal routes for picking.

The list of orders is received at the warehouse. Then, Sienzi's operations officer requests an optimized picking solution from the AI-based system. The system provides the solution in real time or in a few minutes, and it is then given to the picker.

The study setup is designed in three modes: traditional single-order-based pick rounds, order batching, and batch-tunnel optimization. The baseline mode was single-order-based pick rounds starting from the collection point, picking items from the shelves for a single order, and bringing the electrically powered reach truck forklift back to the starting point. Using the forklift, the picker lifts a basket with a capacity of 40 items, picks the items, and places them in the basket. The picker repeats the process if the entire single order is not picked in one round due to picking capacity limitations. In the order batching mode, the Joint Order Batching and Picker Routing Problem (JOBPRP) was used (Valle et al. 2017; Gils et al. 2019), which integrates the Order Batching Problem (OBP) (Gademann et al. 2001) with the Picker Router Problem to optimize picking several orders at a time in the shortest distance. For the batch-tunnel optimization mode, an additional tunnel was added to the simulations to evaluate its resulting impact. The tunnel was added to batch optimization to address the limitations imposed by the layout structure on optimization capacity. By incorporating an imaginary pick tunnel positioned across the aisles in the upper section of the warehouse layout, the aim was to evaluate the potential of reducing total travel distance in theory (see Vaughan 1999). The tunnel's position was carefully selected to minimize its impact on the aisles and to be near the warehouse wall. Orders used for the study's analysis were randomly selected orders. Conducting real picking in the first two modes (i.e., single order-based pick rounds and order batching) and simulated picking in the third mode (i.e., batch-tunnel optimization), underpinned the empirical ground for the qualitative and quantitative analyses.

4.3 Quantitative approach

Order picking performance was assessed by aggregating total travel distances and the travel time required to pick all orders. Travel time is considered a waste in the context of order picking (Bartholdi and Hackman 2005), and reducing travel time can lead to cost savings and improved service levels (de Koster et al. 2007). Comparative analyses were made based on the total distance and time spent between baseline order-picking rounds, order-batching optimization, and order-batching optimization with an extra pick tunnel. Three hypotheses are proposed to test the effectiveness of the AI-based system in the warehouse's order-picking process. The first two hypotheses test whether travel distances have been improved, while the third hypothesis examines changes in travel time, as follows:

> H_{1a}: AI-based order-batching optimization reduces travel distance compared to traditional single-order picking in the warehouse.

> H_{1b}: AI-based order-batching optimization with a tunnel simulation reduces travel distance compared to traditional single-order picking in the warehouse.

> H_2: AI-based order-batching optimization reduces travel time compared to traditional single-order picking in the warehouse.

Numerical data were collected by conducting systematic direct observations in the warehouse during single-order picking and picking with AI-based order-batching optimization. One of the researchers accompanied the warehouse picker during order-picking activities to ensure real-time data collection with high accuracy and reliability in measuring travel distances employing the warehouse layout and a stopwatch to calculate travel time. For the third stage, the data collection involving the AI-based order batching with an additional pick tunnel was conducted using simulation. The results obtained from the warehouse picking operations were subjected to statistical analysis to examine the potential significant differences between AI-based picking and traditional order picking in terms of time and distance. Descriptive statistics for time and distance were calculated for both the order-picking and batch-optimization groups. The selection of statistical tests was guided by the need to ensure rigorous and valid comparisons between groups. Initially, a t-test for two independent samples was considered to assess the significance of differences between the groups in line with the suggestions advanced by Hair et al. (2019). However, nonparametric alternatives were also considered, given the potential violation of the normal distribution assumption, which could result in type I errors (Field 2013).

Prior to conducting the statistical analyses, the normal distribution was assessed for traditional single pick rounds and order-batching optimization using the two-sample Kolmogorov–Smirnov test (Tabachnick and Fidell 2013). The results indicated that there was a significant deviation from the normal distribution for both time ($p=0.036$) and distance ($p=0.000$). Additionally, single pick rounds included 29 pick rounds, while AI-based order-batching optimization had 25 rounds, with each group having fewer than the threshold value of 30 observations. According to Hair et al. (2019), in samples of 50 or fewer observations, especially when the sample size in each group is below 30, significant departures from normality can greatly affect the results. Therefore, a nonparametric test was more applicable because the data deviated from the normal distribution, and the number of observations was insufficient (Dodge 2008; Hair et al. 2019). The Mann–Whitney U test, the nonparametric analogue of the t-test for two independent samples, was employed to investigate whether there is a difference between the groups regarding distance and time (Sheskin 2020). Statistical significance using a p-value less than 0.05 was considered.

Further analysis focused only on the travel distance metric and was conducted after the tunnel simulation because the simulation could not objectively and realistically cover time. This stage of the analysis used one-way ANOVA for three groups: single-order picking, (AI-based) order-batching optimization, and (AI-based) order-batching optimization with an additional pick tunnel. Prior to conducting the statistical analyses, the normal distribution was assessed using the Kolmogorov–Smirnov test. The results indicated that there was no significant deviation from normal distribution for travel distance ($p=0.200$). Additionally, skewness and kurtosis values of the travel distance variable were checked to meet normal distribution assumptions. According to Kline (2011), the absolute value of skewness should not exceed ± 3, and the absolute value of kurtosis should not exceed ± 10, to avoid significant deviations from normality in the data. Values exceeding these thresholds may indicate substantial departures from normality in the data. The skewness and kurtosis values of travel distance were determined as 0.808 and 2.883, respectively, falling within the acceptable threshold values of less than 3 and 10, respectively. Based on these results, a parametric test (a one-way ANOVA test) rather than a non-parametric alternative was utilized to check if the travel distance scores of these three groups showed a significant difference (Kline 2011; Hair et al. 2019).

In conclusion, the study's methodological approach incorporates robust statistical techniques to account for potential violations of normality and small sample sizes. Using the Mann–Whitney U and one-way ANOVA tests, the study ensures that the comparisons between traditional and AI-based order-picking methods are consistent and valid.

4.4 Qualitative approach

This study also examines the AI-based order-picking adoption in the case of Sienzi from a qualitative perspective. The data collection included a combination of interviews, direct observations conducted by two research team members at the warehouse site, seven meetings, and communications through WhatsApp and email, supplemented further by documents from Kairos. These data collection methods are particularly valuable for case studies and qualitative research (Barrett and Twycross 2018; Yin 2018).

The interview protocol was developed based on key themes from the pertinent literature, which guided the development of the interview questions. Key aspects of the warehouse's order-picking activity were discussed in the interviews, including operational efficiency, system integration, employee training, and the overall impact on warehouse performance. The qualitative approach involved 11 semi-structured online and face-to-face interviews. Nine of these interviews were conducted individually, while two were group interviews. Participants included eight representatives from Sienzi, one from Select, and two from Kairos. This triadic approach facilitated a comprehensive understanding of diverse stakeholder perspectives. Face-to-face meetings took place in the headquarters of Sienzi and Select, and only meetings with Kairos' representatives were conducted online for convenience. Prior to each interview, participants were informed about the study's objectives, and participants' consent to record the interviews was obtained beforehand. The group interviews exclusively involved a mix of managerial and operational-level participants from Sienzi. Group Interview 1 comprised four managerial-level participants, and Group Interview 2 consisted of two operational-level employees. Details of the interview specifics and participants are presented in Table 1.

The interview questions were developed based on concepts from the literature (see Table 2). In total, 22 concepts formed the basis for all the interview questions. Of these, nine concepts targeted general inquiries from Sienzi, while the remaining 13 concepts explored specific topics drawn from past literature. These 13 concepts were examined in relation to the impact of the AI-based system on them.

One of the key 13 concepts is *traveling time*, which constitutes the largest proportion of the entire picking time (de Koster et al. 2007; Tajima et al. 2020). Our case presents the AI-based system specifically designed to affect the traveling time while optimizing traveled distances. Hence, this study selected traveling time for evaluation among the various time-consuming sub-activities. The next concept is *pickers' wellbeing*, which involves various components such as workers' health, motivation, and comfort (Larco et al. 2017; Richards 2018; Glock et al. 2019; Gajšek et al. 2021).

The third concept focuses on *picking quality* in terms of the number of damaged or incorrect orders (Kiefer and Novack 1999; Richards 2018). The fourth and fifth concepts center on *operational and data flow control* (Richards 2018) and *documentation*, which relates to the format and quality of checklists and printouts (Kiefer and Novack 1999; Richards 2018). The sixth concept refers to supply chain *actors' collaboration*, which is manifested in the degree of partnership and cooperation (Richards 2018). The seventh concept addresses *cost* changes due to the arrival of the AI-based system, whether increasing or decreasing (Kiefer and Novack 1999; de Koster et al. 2007; Richards 2018). The eighth refers to the changes in the *physical space occupation* of the warehouse due to the adoption of the AI-based system (de Koster et al. 2007; Richards 2018). The ninth concept examines *privacy, legal, and security concerns* that may arise when using an AI-based system, such as data protection (Richards 2018). The tenth concept focuses on *ease of use/training*, which

Table 1 Characteristics of interviews

Title of interviewee	Code	Interview number	Interview duration
George Lijo, the CEO and founder of Kairos	Mr. Lijo	Interview number one	61 min, 50 s
		Interview number two	52 min, 49 s
Deputy General Manager in Sienzi	P1	Interview number three	25 min,19 s
		Interview number eight	32 min, 32 s
		Interview number ten	13 min, 23 s
Warehouse Operations Supervisor in Sienzi	P2	Interview number four	22 min, 42 s
Picker in Sienzi	P3	Interview number five	19 min, 57 s
Group Interview 1- General Manager and Founder, Deputy General Manager, Warehouse Manager, Manager Assistant in Sienzi	P4	Interview number six	40 min, 54 s
General Manager and Founder of Sienzi	P5	Interview number seven	33 min, 46 s
Group Interview 2- Operations Officer and Picker	P6	Interview number nine	50 min, 27 s
Mr. Gökhan, the CEO of Select	P7	Interview number eleven	34 min, 40 s

revolves around the readiness of workers to use the AI-based system (De Vries et al. 2016; Richards 2018; Pasparakis et al. 2023). The eleventh concept concerns *system interoperability*, which focuses on the degree of match between AI-based systems and the current technological infrastructure of the warehouse (Mahroof 2019). The twelfth concept considers *items accessibility* for the workers in the warehouse (Richards 2018). Finally, the thirteenth concept refers to the *environmental impact* that an AI-based system can generate in the warehousing process, such as changes in energy consumption (Đukić et al. 2010; Richards 2018; Bartolini et al. 2019).

We used the Gioia approach to conduct qualitative analyses (see Gioia et al. 2013). Through this approach, we developed a data structure (see Tables 5, 6, and 7) that made it easier to track the process of converting interview data into final themes. Drawing on Gioia et al. (2013) and consistent with Tables 5, 6, and 7, the data structure starts by developing 1st-order concepts from the raw interview data. Then, concepts filter into 2nd-order themes based on relevance and characteristics. Third, they emerge as aggregate dimensions of benefits, challenges, and critical success factors. A team of two authors undertook all three steps in developing the qualitative analysis and data structure to ensure a more reliable investigation. The development of the 1st-order concepts began with scanning the raw interview data, followed by marking and coding relevant parts of the texts based on the reviewed literature and research focus. Initially, each author independently scanned and marked the raw interview

Table 2 Concepts discussed in interviews

Extracted concepts	Driving references
Picking time: traveling time	de Koster et al. (2007), Richards (2018), Tajima et al. (2020)
Pickers' wellbeing	Larco et al. (2017), Richards (2018), Glock et al. (2019), Gajšek et al. (2021)
Picking quality (Number of damaged/incorrect orders)	Kiefer and Novack (1999), Richards (2018)
Operational and data flow control	Richards (2018)
Documentation	Kiefer and Novack (1999), Richards (2018)
Actors' collaboration	Richards (2018)
Costs	Kiefer and Novack (1999), de Koster et al. (2007), Richards (2018)
Physical space occupation	de Koster et al. (2007), Richards (2018)
Privacy, legal, and security concerns	Richards (2018)
Ease of use/training	De Vries et al. (2016), Richards, (2018), Pasparakis et al. (2023)
System interoperability	Mahroof (2019)
Items accessibility	Richards (2018)
Environmental impact (green picking)	Đukić et al. (2010), Richards (2018), Bartolini et al. (2019)
Number of shifts per day	General question
Hours per shift	General question
Number of pickers in total	General question
Picker's salary	General question
Picking vehicle's specificities	General question
Customer orders' average size	General question
Customer orders' volume size	General question
Picking cart's capacity	General question
Picking approach	General question

data. The outcomes were then compared and discussed by the research team members, resulting in the emergence of the final 1st-order concepts. The authors subsequently grouped these concepts into 2nd-order themes. A similar grouping process was used to develop the aggregate dimensions.

The transparency provided by Gioia's data structure makes it a valuable methodological tool for conducting and presenting qualitative analyses, addressing the critique of data cherry picking often associated with qualitative methods (Gioia et al. 2013). Gioia et al. (2013) explain their intention behind the Gioia approach, noting that it aims to avoid cherry-picking quotations from reports, relying on clever explanations, and wrapping insights in appealing labels. The Gioia method provides a reasonable degree of visibility, enabling input tracing from raw data to the final output.

5 Results

This section presents the study results, integrating quantitative and qualitative findings to ensure coherence and depth. Numerical data were collected through systematic observations in the warehouse. In conjunction with these quantitative findings, qualitative insights were obtained from interviews and other relevant sources. After presenting the quantitative results, the qualitative results are provided. Together, these results provide a comprehensive view, with further synthesis offered in the discussion section.

5.1 Quantitative results

The traditional order-based single pick rounds consisted of 29 pick rounds, which were reduced to 25 batches in 25 rounds using order-batching optimization. Table 3 provides descriptive statistics over the baseline and the other two optimized order pickings at an aggregate level.

Table 4 compares travel distances and time in the traditional single-pick rounds, order-batching optimization, and order-batching optimization with an extra pick tunnel. Batch-picking optimization reduced the travel distance by 27.25% compared to the baseline single-pick rounds. The results of the order-batching examination show the importance of order batching in improving picking efficiency. An additional 13.91% reduced the travel distance with an extra pick tunnel. Moreover, the result of the simulation study shows the importance of and the relationship between order-batching optimization and cross aisles in improving routing flexibility and travel distance reduction. Regarding time, the batch-picking optimization gave a 22.82% reduction in travel time.

Implementing the system in the warehouse's picking operations resulted in notable improvements in efficiency, specifically in terms of travel time and distance. To test the effectiveness of the AI-based system, Mann–Whitney U tests were conducted

Table 3 Descriptive statistics

	Order-based pick rounds	Order batching optimization	Order batching optimization with extra pick tunnel
Number of rounds	29	25	25
Shortest distance	172.05*	134.99	119.69
Longest distance	417.29	272.76	225.57
Total travel distance	7279.30	5295.30	4558.71
Average distance	251 ± 47.75	211.81 ± 33.88	
Median distance	249.72	211.86	
Shortest travel time	02:16**	01:45	–
Longest travel time	04:03	04:32	–
Total travel time	97:07	74:57	–
Average time	3:13 ± 0:48	2:83 ± 0:07	
Median time	3:23	3:04	

*: Meter. Centimeter, **: Minutes: Seconds

Table 4 Travel distances and lead time in the traditional single pick rounds, order batching optimization, and order batching optimization with an extra pick tunnel

Order-based pick rounds		Order batching optimization			Order batching optimization with extra pick tunnel	
Original distances	Picking time (min:sec)	Optimum distances	Picking time (min:sec)	No. of orders	Batch picking of	Optimal distance
245.4	03:55	227.68	03:05	3	SP30, SP26, SP22	179.14
290.86	03:57	203.35	03:51	2	SP15, SP4	223.34
193.03	02:51	187.44	03:56	3	SP24, SP12, SP7	196.42
185.75	03:12	221.97	02:42	3	SP11, SP14, SP2	214.3
269.78	03:20	211.7	03:06	2	SP2, SP28	222.74
231.56	03:10	210.43	03:11	3	SP28, SP5, SP19	217.26
220.46	03:54	218.2	03:09	3	SP19, SP28, SP5	138.76
191.65	02:50	220.34	02:56	4	SP9, SP10, SP6, SP8	150.1
228.5	02:40	216.68	03:13	3	SP8, SP10, SP6	225.57
245.68	03:24	222.59	02:48	5	SP6, SP10, SP8, SP29, SP16	172.62
287.2	03:51	197.99	02:44	2	SP16, SP29	169.06
212.32	02:19	156.77	01:57	1	SP16	160.73
201.96	03:35	228.51	03:12	3	SP22, SP26, SP30	192.8
249.72	03:44	149.69	01:45	1	SP15	121.78
316.62	03:23	257.63	02:23	3	SP24, SP12, SP7	166.88
259.65	03:45	134.99	02:18	6	SP22, SP26, SP30, SP23, SP9, SP13	137.95
295.13	04:03	211.86	04:32	5	SP24, SP7, SP20, SP1, SP27	204.81
253.82	03:20	257.12	02:43	3	SP13, SP23, SP9	202.16
244.74	03:02	211.71	03:58	3	SP27, SP1, SP20	189.76
258.52	02:53	210.49	03:02	4	SP13, SP23, SP9, S3	164.67
255.41	03:02	164.78	03:46	2	SP27, SP20	119.69
234.59	03:56	210.66	02:39	2	SP18, SP3	220.25
241.64	03:37	225.91	03:16	3	SP18, SP3, SP17	177.65
172.05	02:16	272.76	02:41	2	SP17, SP21	183.96
253.39	03:41	264.05	03:04	4	SP21, SP17, SP11, SP14	206.31
260.62	03:02					
304.33	03:59					
257.33	02:41					
417.29	03:45					

to compare the travel distances and times between the different picking methods. The choice of the Mann–Whitney U test was guided by the non-normal distribution of the data and the small sample sizes, as confirmed by the two-sample Kolmogorov–Smirnov test.

The median travel time difference between order-based pick rounds and order-batching optimization using AI was calculated as 00:19. Although a reduction in time was observed after the implementation, the change was not statistically significant (U = 252.50, $p = 0.056$). Hence, H_2 is not supported. However, a certain optimization level is achieved in time, despite not reaching acceptable statistical significance. The median travel distance difference between order-based pick rounds and order-batching optimization using AI is calculated as 37.91. AI implementation showed a significant reduction in terms of traveled distance ($U = 177.00$, $p = 0.001$). Hence, H_{1a} is supported.

Having found a significant difference in travel distance between order-based pick rounds and AI-based order-batching optimization, further analysis was conducted using the tunnel simulation to detect possible differences among single pick rounds, AI-based order-batching optimization, and AI-based order-batching optimization with an additional pick tunnel. A one-way ANOVA test was conducted to determine whether these three groups have statistically significant differences in travel distance. The ANOVA analysis showed statistically significant differences between the groups with the value of $F(2.76) = 21.05$, $p < 0.001$.

In the ANOVA test, homogeneity in the variances of groups is expected, and it is checked using Levene's test. If Levene's test is non-significant (the *p*-value is greater than 0.05), the homogeneity of variance assumption is met (Kline 2011). In this case, the significance level of the F statistic produced by ANOVA checks the differences between groups (Field 2013). After finding the differences between groups, post-hoc multiple comparison tests can be used to determine which specific group differs significantly from the others. Bonferroni's and Tukey's tests both control the Type I error rate effectively but are considered conservative tests, meaning they may lack statistical power. Bonferroni's test is more powerful when the number of comparisons is small, while Tukey's test is more powerful when comparing a larger number of means. Bonferroni's test can be used effectively if the sample sizes of the groups are small and reasonably equal, and the homogeneity of variances is not violated (Field 2013). Therefore, Bonferroni's test is utilized for post-hoc tests to compare the groups. Bonferroni's test showed statistically significant differences in travel distance between group comparisons:

- AI-based order-batching optimization significantly reduced travel distance compared to traditional single-pick rounds (Mean difference = 39.19, $p = 0.001$).
- AI-based order-batching optimization with an additional pick tunnel significantly reduced travel distance compared to traditional single-pick rounds (Mean difference = 68.65, $p = 0.000$).
- AI-based order-batching optimization with an additional pick tunnel significantly reduced travel distance compared to AI-based order-batching optimization (Mean difference = 29.46, $p = 0.028$).

The analysis concluded that AI-based order-batching optimization with an additional pick tunnel ($M = 182.35$, $SD = 31.96$) and AI-based order-batching optimization ($M = 211.81$, $SD = 33.88$) resulted in statistically significant and lower travel distances compared to traditional single-pick rounds ($M = 251.00$, $SD = 47.75$). Therefore, hypothesis H1b is supported.

5.2 Qualitative results

The results of the qualitative study, conducted using the Gioia approach, are illustrated in Tables 5, 6, and 7, highlighting the benefits, critical success factors, and challenges associated with adopting the AI-based system in the warehouse.

Table 5 Benefits

1st order concepts	2nd order themes	Aggregate dimensions
• The system shortens the picking process a lot	Optimal routing solution	Travel distance and time reduction
• It saved time to enter the orders as a single order by combining the orders		
• There was a reduction in order picking time		
• Saving time, picking orders faster, and making the shipment faster affect both the customer and the warehouse in a positive way		
•… going to the same location… shortens the picking process		Higher order-picking simplicity
• It shortens the pick route of the vehicles		
• When it was batched, it had an advantage in receiving the order from the same location		
• The system made order picking faster. Things have gotten faster		
• Each line they had to print… and do the paper pin and clip and so on and obviously that lot of clearance could happen there	Less complex documentation	
• The documentation of artificial intelligence tells us which location we can go to and which orders we can take at the same time, how we can draw the fastest path		
• Such an advantage in documentation… directly reduces time, reduces documentation, and gains speed		Improved documentation
• The system has made the documentation process smoother		
• Instead of checking the order list one by one… we can find the material directly		
• We could see the materials more easily because there was only one page		
• The system reduced documentation and consolidated locations	Lower use of order list printouts stationery	
• The number of check lists reduced to close to 30 to 50% because before the picker was taking number of separate orders in separate checklists		
• Traditionally, sometimes, checklist was made only for one item as it was the only customer order		
• This method reduces the list of four checklists to one		
• The number of documents was reduced		
• There are fewer wrong orders. It became harder for us to get the wrong material	Lower number of errors and wrong orders	Higher order-picking accuracy
• It had a positive impact on the number of wrong orders		
• They said wrong orders actually decreased		
• The use of this system… prevents incorrect order picking		
• There were no erroneous orders		
• There were no disruptions or problems in these order pickings		
• Since they had the order list in a more organised way, the possibility of picking the wrong product was also reduced		

Table 5 (continued)

1st order concepts	2nd order themes	Aggregate dimensions
• They have to use a lot less electricity for the truck • I can say that it has positive effects on fuel, electricity… costs • There has been less energy consumption because things have gotten faster • I think there will be a reduction in energy costs • As the time we do not use the machine increases, our consumption decreases • It provides fuel advantage as it shortens the road route of the vehicles	Lower energy cost for truck traveling	Cost reduction
• For example, while the machine was working for 10 min before, now it works for 5 min • Less use of the machine… when we turn off the machine… after this fast-picking process • If you had to repair or replace the machine… they extend the lifetime… so we say the cost affordance • Reductions in time, less use of the machine…	Lower truck maintenance cost	
• For example, we collected the order and there was a time gap… so we will complete other tasks with the free time • We can transport more material in less time • We aim to increase our earnings with new projects in our colleagues' free time • This picking optimization… is of course effective in terms of saving… the time of the personnel	Lower labor cost	
• I can say that it has positive effects on… documentation/ stationery costs • It has an impact on stationery costs • The system reduced documentation… • Each line they had to print… and do the paper pin and clip and so on and obviously that lot of clearance could happen there	Lower stationary cost	
• The pickers feel more comfortable •…less fatigue of the staff, more accurate guidance by artificial intelligence • "… shortened picking time… satisfied the personnel" • It has a very positive effect on the colleagues on this task • It's just the perception of their (employees') welfare gets improved… So, they are qualitative improvements • Item picking and searching became easier	More comfort	Employees' well-being
• We were going to the same location 10 times…now we…. picked them in one go…. The pickers felt better about picking • Instead of going to the same location 10 times and picking again and again, being able to pick 10 orders from that location… • They had to go spend so much time to do repetitive tasks for different orders. Now, they go for once… pick for all the customers	Less boredom	

Table 5 (continued)

1st order concepts	2nd order themes	Aggregate dimensions
• There has been less energy consumption because things have gotten faster • It provides fuel advantage • It has a positive (environmental) impact as it saves fuel and electricity • We can say that energy has been saved • Our (energy) consumption decreases and this affects us positively • This picking optimization… is of course effective in terms of saving time, fuel consumption…	Lower energy consumption	Positive environmental impacts
• For example, while the machine was working for 10 min before, now it works for 5 min • We were going to the same location 10 times and pick differently, and now we combined 10 locations and picked them in one go • Since the order is collected faster, we turn off the machine for 10–20 min •… it shortens the road route of the vehicles • Machines last longer lifetime	Longer machine's lifetime	
• The system reduced documentation… • The biggest impact is on documentation • The main goal of the system is to… reduce documentation • It reduced lots of paperwork… collecting the data and structuring the way we want… improved their discipline anyway	Lower paper consumption	

The study results reveal that the AI-based system provides several benefits for warehouse picking activities. One major benefit is the *reduction of travel distance and time*. Due to the optimal routing solutions offered by the AI-based system, pickers travel shorter distances and spend less time completing the same picking tasks, compared to the traditional approach without the AI-based system. Participants in the study acknowledged the benefits of optimized pick routes generated by the system. P1 states: "*the system shortens the picking process a lot... as it shortens the road route of the vehicles*". P3 argues that: "*The system made order picking faster. Things have gotten faster.*" This paper's quantitative results also corroborate the time and distance reduction.

Furthermore, the AI-based system has enabled *improved documentation* in the warehouse. Documentation is now more organized, with a reduction in the use of order list printouts and stationery. P1 emphasized that: "*the system reduced documentation and consolidated locations.*" Traditionally, each customer order had its own checklist and printouts, which Sienzi would compile to plan daily pickings. The AI-based system, however, combined orders and generated a checklist of batched items to pick. Compared to the traditional approach, the system produced significantly fewer checklists by batching single orders and reducing line space between suggested pick rounds.

Additionally, the AI-based system has simplified documentation. This reduction in complexity is partly due to a smaller number of checklists, as well as changes in the

Table 6 Critical Success Factors

1st order concepts	2nd order themes	Aggregate dimensions
• Usually, these sorting or rearranging is there, if they do the batching from the beginning but since they do not, this comes as an additional	Functional integration	Strategic alignment
• You do pick optimization, batching optimization you do per customer, arranging, and then you also do the sorting		
• In projects with shipments to different points, after joint collection (batching), they (parcels) need to be separated during shipment		
• There will be a manual sorting done by manpower. If each parcel has a separate barcode…		
• When there are mixed orders (from different customers), the collected parcels need to be sorted		
• Saving time, picking orders faster and making the shipment faster affects both the customer and the warehouse in a positive way	Strategic fit	
• We can transport more material in less time		
• Since the orders were picked randomly (in the past), it was then needed to go to the same location for the same item for several times		
• There will be a reduction in costs		
• We picked the orders in a shorter time and distance		
• It has a positive (environmental) impact as it saves fuel and electricity		
• The pickers feel more comfortable		
• I think with a change in the entry stage of the products, the picking processes can be made more suitable for this method	Business process re-engineering	
• Revisions can be made on order sorting… new software or codes can be developed, or better ideas about sorting in the picking area can emerge		
• There can be updates for sorting that can be added to the software		
•…. change here is that now we are labeling the product when we collect it		
• The structural change, or item location or even process change, there are many ways to do the thing		
• After switching to this type of system… there are these labels on the products, and our work became easier		

Table 6 (continued)

1st order concepts	2nd order themes	Aggregate dimensions
• The system did not cause us any problems and worked well with other systems • It was integrated with (our warehouse program) and worked in harmony • The software updates on our system… worked harmoniously • The system Sienzi Logistics using is warehouse management system or ERP… they needed to integrate API into their system • It is an adaptable project to the logistics programs that we use and that are used in warehouses	Technological integration and interoperability	Structural alignment
• It is usually needed to have direct communication • I couldn't get the efficiency I wanted. I wish we could communicate more… • External factors… the situation of our company caused communication to remain a little weaker in something that could have been much more productive	Communication	Operational Alignment
• Sienzi Logistics's ERP developer (Select) needed to connect to me (Kairos) to understand the correct usage of the data • It still took time to connect to the vendor (Select) • It benefits if Select connects to our technical guys to work together… but there is always something in the process or configuration… then they had to get help from Sienzi Logistics and they need to configure it correctly	Triadic (supply chain) collaboration	
• We were provided with the necessary information through trainings • I think the system can be improved by providing training to the pickers and the operator • Using the system becomes easier with the training received • The learning process was easy, there is nothing very challenging • Select provided trainings in a certain period of time	Education and training	
• The maintenance is included in Kairos's monthly fee • Mr. Gökhan even came here from Select for the continuation of the application	Technological maintenance	
• We had to share some documentation to make the system usable • We did this (data sharing) with the permission of our companies • We had to share some information • We just follow the regular common approach of data sharing mechanism	Data Sharing Permission	Data Privacy
• We have a confidentiality agreement with them • This is already a confidential situation… as there was no data loss at the entrances and exits • There was a facilitated agreement between all 3 of us in the very beginning of the project • We sign an NDA just to be sure we are on the safe side	Confidentiality Agreement	
• It has not raised any privacy or security concerns • We work within the scope of the law on the use of personal data • There were no legal problems… we did not have any data loss or data leakage • We shared (data) in accordance with legal procedures	Privacy and Regulatory Compliance	

Table 6 (continued)

1st order concepts	2nd order themes	Aggregate dimensions
• It is just a matter of thinking holistically and being able to accept the changes • Just as human beings basically resist everything new, a new organization, a new technological data entry is first met with resistance in our company as it is everywhere… resistance is gradually broken • Technology must enter… warehouse management • Using technology like this is the right thing for the top executives of a company	Willingness to make changes	Managerial commitment

checklist format. Previously, checklists included only locations and products, leaving pickers to rely on their own judgment to determine the picking sequence. With the AI-based system, checklists now include suggested optimal routes for picking each item.

Another benefit is the *positive environmental impact*. The use of the AI-based system reduces energy consumption for the picking activity because the electric reach truck travels shorter distances due to batched picking and optimal routing. This approach replaces the previous order-by-order picking and manual routing methods. In this regard, P1 states that: "*It has a positive impact (on environment) as it saves fuel and electricity……In short, I can say that it has a positive effect on fuel and electricity….*" In addition, batched picking and optimal routing allow the truck to accomplish the same tasks with less use, which contributes to a *longer lifespan for the truck* and reduces the need for repair and replacement materials.

Concerning the environmental impact, Mr. Lijo mentions that: *"there is saving of energy also… longer lifetime… to repair or replace the machine."* Moreover, P2 states that: "*Saving time, picking orders faster and making the shipment faster affect both the customer and the warehouse in a positive way. Since the orders are picked faster, when we turn off the machine for 10 to 20 min, for example, there is no electricity consumption. As the time we do not use the machine increases, our consumption decreases.*" This is consistent with the findings of De Giovanni (2021) and Gallo et al. (2023) regarding the positive environmental impact of AI on supply chains. Additionally, longer truck lifespans help reduce warehouse costs. Finally, reduced printout requirements in AI-based systems lower paper consumption, further benefiting the environment.

In some areas, empirical evidence has shown an increase in costs, which we have included in the challenges section of our study. However, in other areas, costs have decreased, which we have categorized as benefits. Specifically, the AI-based system in the warehouse has reduced time and distance in the picking process, resulting in lower energy costs for truck travel, reduced truck maintenance costs, and lower labor costs for this labor-intensive activity (Richards 2018). Additionally, improved documentation has led to lower stationery costs. The cost reduction benefit facilitated by the AI-based system and its systematic approach align with findings from previous studies (Choy et al. 2017; Pournader et al. 2021).

Furthermore, with optimal picking routes suggested in the checklist, pickers no longer need to consider the travel routes. Additionally, batch picking eliminates the

Table 7 Challenges

1st order concepts	2nd order themes	Aggregate dimensions
• We must write a new API for Kairos • At first the system was not fully integrated, but this can be seen in every new installation process • The integration process was difficult • It took some time, but there is no problem in the working phase. Every program takes time during the integration phase…	Initial mismatch and a struggle to adapt to the new program	Structural alignment
• It benefits if the Select connects to our technical guys to work together • Their engineer never talked to my engineer. I only talked to their manager • When it comes to technical subscription ation it is good to have technical people understand our discussion	Lack of direct communication at technical level	
• There was limit at exchange of information what exactly and how they do versus what we do • There always will be issue…because of the lack of communication • We did not have that discussion in the design issue •…. the pandemic started…. we were in a chaotic environment • They implemented according to their understanding… because of the lack of the communication	Lack of robust Communication	Strategic alignment
• We did not have that discussion in the design issue… • We didn't design these things beforehand. We just implemented the very basics… • If we did discuss how they would like to do, including the possibilities that is in the system…	Lack of Joint Planning	
• We only focused on the picking part and started the process from there •…you understand and design the system that is optimal for it • You think through the process or what you are trying to achieve and then you design it for it • They also needed to understand the process and these configurations…	Poor pre-implementation business review	
•…I just picked a method and then we implemented it • There would be a second task in the sorting area because of the picking procedure • If we did discuss how they would like to do, including the possibilities that is in the system…	Limited understandings of operational dynamics	
• There was a process of reading and perceiving the documentation provided by the program • Information flow was required both to know how to use the program and to read the documentation correctly •…We switched to a different documentation from the documentation we were used to…	Documentation Approach	Operational alignment

Table 7 (continued)

1st order concepts	2nd order themes	Aggregate dimensions
• More forward-looking investments can also be made • A revision can be made regarding order sorting… these can be extra costs • So, there are many many more things you could do but it also comes with the cost of rearranging everything and stopping their operation and all • Building a tunnel would be sacrificing our source of income	Business adjustment cost	Costs
• If they want to use it, they need to pay the monthly fee • Normally you have an implementation fee plus monthly fee	Implementation and subscription cost	
• The pandemic was a situation that we were never prepared for in our lives • Warehouses are now much more needed… So, we continued to work, but there was chaos • The company was actually so busy with its own operational processes • We were in a very serious chaos • We could not make this move because the loss of storage space in that area would bring us a more chaotic environment	Fatigue from heavy daily workloads	Resistance to change
• There are no changes that can be made on the existing system we use • The introduction of artificial intelligence may have limited their (pickers) space at this point… because it directly tells them what to do	Fear of losing freedom	

need to revisit the same location multiple times for different orders. Together with reduced travel distances and time, these factors have contributed to a *simpler order picking experience* at the warehouse. In this regard, P3 states that: "*it is better this way, and the complexity has been eliminated…we no longer search for the materials in the order one by one… The system made our work easier. We can easily find the materials on the shelf thanks to the system.*"

The *higher order-picking simplicity* has helped reduce errors and incorrect orders, leading to *higher order-picking accuracy*. P2 states that: "*I can say that it affects positively, because when you do business in a non-systematic way, in old terms, in a chaotic way, there is a lot of room for error.*" According to Setayesh et al. (2022), while pick errors can significantly impact operational success in manual picking, sufficient attention has not been given to enhancing pick quality. In this context, the AI-based system utilized in our case demonstrates fruitful results for improving picking accuracy. Our findings align with De Giovanni (2021), showing that AI implementation can reduce error rates and positively impact overall supply chain performance.

The final benefit is improved *employee well-being*. Completing tasks more quickly, accurately, and with simpler, more straightforward documentation has helped staff feel more comfortable. This improvement is particularly evident among pickers, who now experience less boredom from repeatedly visiting the same locations to pick items listed on different order lists. P1 emphasizes that: "*the pickers feel more comfortable*" and "*… shortened picking time… satisfied the personnel.*" Similarly, Grosse (2024) supports the idea that AI-based picking route optimization enhances employee well-being.

When the AI-based system was planned for integration into warehouse operations, a technological matching between the existing ERP system and the new AI-based system was necessary to establish the API. This necessity can be viewed as *structural alignment*, as suggested by Peng et al. (2021), involving architectural integration and interoperability between new and existing technologies. Select is responsible for integrating the ERP with the AI-based system. In this regard, Mr. Lijo states that: *"the system warehouse is using its Warehouse Management System or ERP provided by Select, and to use the logic, they needed to use the API, or they needed to integrate API into their system. Otherwise, how do they use it? This is not a standalone solution, so they need to call the API and display it in their system for pickers to use the algorithm."*

Despite the eventual success of structural alignment, which refers to the integration and interoperability of technologies, there was an initial mismatch and a struggle to adapt to the new program. This challenge may have stemmed from the novelty of the API protocol that needed to be developed between the AI-based system and ERP. Select had previously established APIs with Sienzi's customers to integrate their orders into the ERP. However, the AI-based system, with functionalities different from previous ERP integrations, required a new API that had not been developed before. As a result, this requirement prolonged the API establishment process between Kairos and Select. According to P1 and P3, such an initial struggle is common: "*It took some time, but there is no problem in the working phase. Every program takes time during the integration phase, and this is a normal situation."* (P1).

Nevertheless, better communication between Kairos and Select could have reduced the time required for technological integration. During the project, Select experienced employee turnover, leading to a shortage of relevant personnel. Replacing these employees proved challenging, especially in finding suitable software engineers in Türkiye. As a result, Select struggled to maintain sufficient personnel for timely and effective communication during the technological integration. Although direct communication occurred at the business/managerial level, technical-level communication was largely lacking, which slowed the pace of integration– *"... their engineer never talked to my engineer. I only talked to their manager."* (Mr. Lijo). Ultimately, the issue was resolved when proper communication took place. In this regard, Mr. Lijo explains: *".... they had to redo it, but then I guided them how to do it or how to use API properly, but, in any case, the second time, everything was OK."*

Operational alignment is another facet that complements structural alignment. It focuses on the flow of activities and processes involved (Maes et al. 2000; Peng et al. 2021). This alignment involves all three primary actors in the project—the AI-based system developer, the warehouse, and the ERP developer—emphasizing the importance of triadic collaboration. Furthermore, communication is a central element in achieving operational alignment (Luftman et al. 1999; Maes et al. 2000). In the long term, another essential aspect of operational alignment is ensuring the continuous, optimal functioning of the AI-based system in the warehouse, achievable through technological maintenance. Kairos has included maintenance service costs in its monthly subscription fee.

Despite its importance, operational alignment has encountered challenges related to changes in the documentation approach. *"There was a process of reading and* *perceiving the documentation provided by the program. Because we switched to a different documentation from the documentation we were used to, that part was a bit difficult, if you recall…. Our flow of using the program has also changed. How we normally transcribe in the program differs from how we transcribe now. The answer given by the program is different."* (P1). Such challenges are, to an extent, natural, given that adaptation often accompanies change (Turienzo et al. 2024). Nevertheless, training is important for enhancing workforce usability of new technology (Büyüközkan and Göçer 2018). In this case, training supports understanding the new format of documents (checklists) generated by the AI-based system. The more effective the training, the easier it is to utilize the technology's features (Davis et al. 1989; Zirar 2023). Conversely, as technology becomes easier to navigate, less intensive training is required. For this project, moderate training has been sufficient to enable effective use of the AI-based system. "*In general, you need training for this. But the learning process was easy, there is nothing very challenging"* (P3). Select was responsible for training Sienzi's employees on using the system– specifically, on interpreting the new checklists generated by the AI-based system. This responsibility stemmed from Select and Sienzi's long-term relationship, their proximity within the same city, and Select's role as the first to receive and communicate the new document format from Kairos after the setup process. Select conducted training sessions for Sienzi employees, who then further developed their skills through practice. Subsequently, new hires at Sienzi gained proficiency by learning from experienced colleagues. This reflects effective communication and triadic collaboration among the three parties to meet training needs and address the complexities introduced by changes in documentation.

Another critical factor in the success of the AI-based system in the warehouse pertains to *strategic alignment*, which focuses on ensuring that the adopted technology aligns with the broader goals and strategies of the business across different sectors (Peng et al. 2021). As cited in Gerow et al. (2014), Chandler (1962) defines strategy as determining an enterprise's mission/goals and adopting actions to achieve them. In this context, strategic alignment addresses the match between adopted/adopting technology and the enterprise's goals that it seeks to serve.

Henderson and Venkatraman (1999) contend that strategic alignment involves two domains: strategic fit and functional integration. Strategic fit includes business strategy and IT strategy—that is, how IT strategy can enhance or shape the business strategy. Functional integration refers to the importance of maintaining coherence between technology's capability and the organizational settings. In our case, although the strategic fit was not a major issue, there was a lack of coherence between the business-wide setting and technology's capability, manifested specifically in sorting complications.

Traditionally, Sienzi was picking items order by order, unloading them at the collecting area (i.e., where the distribution company picks up the items), then labeling the unloaded products for the distributor to identify them and put them in the transportation vehicle. The AI-based system provides Sienzi with the picking sequence based on the proximity of the stored items' locations, and the system combines/batches orders from different customers. With these changes in the picking logic, the traditional labeling approach involving product labeling in the collecting area was no longer effective. This was because products were picked in a mixed manner, and the picker in the collecting area could not recognize each product in the pool of mixed products. Consequently, with this traditional approach, time was wasted on sorting each product and labeling it correctly, causing the sorting complication. According to P1: *"However, in projects with shipments to different points, after joint collection (batching), they (parcels) need to be separated during shipment... We lose the time we save on the shelf while sorting during the loading process to the car in picks with different shipment destinations."* The AI-based system's capability for batching aimed to achieve time saving. However, it resulted in the need for additional time and more space in the sorting phase, leading to incoherence and complications with functional integration. This can be attributed to Sienzi's poor pre-implementation business review of possible technology-driven alterations in the warehousing process. Another causal factor is related to the lack of joint planning, which is beneficial in achieving a clearer picture of the wide impact of the AI-based system on the activities and on the possible technological complementarity in tackling the unwanted sorting complication. Joint planning allows the perspectives of each side to be brought closer together, fostering collaboration and creating opportunities to enhance the configuration of the technology for a better fit with the business. In this regard, Mr. Lijo states that: *"Software-wise, we can rearrange the sorting and that is certainly what I meant. We could do it before doing the batching, which would be slightly less improved.... So, this is the part I was saying upon the integration of process; if we did discuss how they would like to do it, including the possibilities that are in the system, we could have implemented it and to get a result. Right? And this was the missing part, but if you understand and design the system that is optimal for it...."* The third element pertains to the lack of robust communication from Sienzi's side. Sienzi could have informed Kairos of the operational steps throughout the picking process, which potentially could have foreshadowed the sorting complication. Sienzi perceived the poor communication and other deficiencies as partly connected to the latest global pandemic. As the project coincided with the COVID-19 pandemic, Sienzi was hit with hectic work routines. First, the pandemic led storing companies to want to keep their stocks in the warehouse because their usual demand was affected, intensifying warehouse operations. Then, employees were contracting COVID-19, putting pressure on other staff to fulfill outstanding tasks. Moreover, they could not dismiss staff due to regulations that imposed financial restrictions on hiring new personnel. They were busy struggling to create an effective schedule and, hence, experienced a shortage of time. All these factors contributed to poor communication and pre-implementation weaknesses. The fourth attributing element is related to the limited understanding by Kairos of Sienzi's operational dynamics. Kairos has customized a system to improve the picking process in Sienzi's warehouse. This customization is associated with comprehending various contextual elements in Sienzi's warehouse, such as the frequency and setup of customer orders, facility layout planning, and the existing technological environment. The operational procedure specific to Sienzi was among the topics that Kairos could have sufficiently understood, which would have led to foreseeing the sorting complication.

To address the issue, Sienzi later changed the labeling approach to reduce time wastage in the collecting area. In this new approach, Sienzi labeled the products while picking (the labels include the product order number). This adjustment ensured that products picked in batches arrived at the collecting area with labels already attached, thereby speeding up the sorting process. This can be included in business process re-engineering (Patrucco et al. 2020), which involves modifying the picking and sorting activities that have contributed to resolving the sorting complication.

Regarding re-engineering and adjusting the business for technological adoption, Sienzi had the possibility of adding an extra tunnel to the warehouse's layout, which would have allowed system-driven route optimizations to provide higher yields. Nevertheless, it refused to do so. Two challenging elements are associated with this refusal: (i) *costs*; (ii) *resistance to change*.

Concerning the first element, there are costs associated with business adjustment that Sienzi could have incurred, reducing the attractiveness of making changes. The construction of a tunnel for route optimization costs both time and money. A tunnel, though well located, occupies space, and Sienzi argues that space is of critical importance. In some projects, it needs to maximize space utilization given the large number of products stored in the warehouse. It contends that, in those projects, losing storage space would cause economic loss. In addition, there are implementation and subscription fees associated with the AI-based system. These costs add to the overall list of expenses that need to be considered by the company.

Moreover, this refusal may be affected by the degree of resistance to change. The chaotic period of the pandemic and its impact on post-pandemic daily workloads caused staff members to experience fatigue and excessive stress. Consequently, they is an inclination to resist any alteration to their work routines, including initiatives such as building an additional tunnel on the warehouse site.

In the initial phase following the introduction of AI-based order picking, another instance of resistance emerged. Despite ultimately recognizing the benefits of the AI-based system for their well-being, initially pickers were reluctant to use it. This was attributed to the system's detailed instructions on the routing process and picking sequence, leading employees to feel that their freedom in picking was now constrained, whereas before they could decide on the traveling routes and picking sequences themselves. This reluctance among pickers hinders the adoption of AI systems for organizations due to certain fears such as loss of job, autonomy and control, which may threaten potential long-term benefits of such technologies (Zirar 2023).

Given a strong commitment and will at managerial level, many barriers can be overcome more effectively by allocating more resources. Mr. Lijo explains: "*They did not look even in the basics. I mean, it's very easy to see the way they are operating in the printout and so on.... it's like the 90 s or 80 s. It's very basic. So, there are many, many more things you could do, but it also comes with the cost of rearranging everything and stopping their operation and all. You heard the guy was saying he was even reluctant to put the tunnel because, you know, he loses the space there.... So it's just a matter of thinking holistically and being able to accept the changes. So, I mean the optimization can do it in many ways. The structural change, or item location or even process change, there are many ways to do the thing.*" The importance of considering costs associated with AI-based systems, as well as the role of managerial willingness, has been highlighted in the pertinent literature (see Merhi 2023).

Furthermore, there is the critical success factor of *data privacy*. As customer orders are now accessible to Kairos, there is a need for permission to share data and to consider privacy issues. There is also a confidentiality agreement with customers. In this regard, P1 explains: *"We had to share some documentation to make the system usable. We had to let you see the products of various companies, we had to share some information. We did this with the permission of our companies."* In addition, data privacy-related matters are dealt with according to government and corporation regulations: "*We work within the scope of the law on the use of personal data."* (P2). Despite the importance and challenging nature of privacy and security in the realm of Industry 4.0 and advanced technologies at supply chain level (Szozda 2017; Luthra and Mangla 2018), in our case, there seems to be no significant complications.

In summary, this study identifies several benefits of the AI-based system for improving the warehousing process. Additionally, a set of critical success factors, along with associated challenges, is identified. While this section has outlined the benefits, challenges, and critical success factors along with supporting arguments, the following section synthesizes these results into integrated insights by discussing their multifaceted components.

6 Discussion

This section provides an integrated discussion of both qualitative and quantitative findings, organized by key themes—benefits, challenges, and critical success factors—in adopting an AI-based system. Rather than separating the findings by data type, this approach synthesizes both under each theme, offering a more cohesive interpretation. With this approach, our discussion aims to provide deeper insights, drawing on the complementary nature of the quantitative and qualitative analyses.

6.1 Benefits

Utilizing the possibilities inherent in AI-driven solutions can be valuable to achieve operational excellence in the warehouses (see, Secundo et al. 2024). Several benefits identified in this study—travel distance and time reduction, improved documentation, positive environmental impact, cost reduction, higher order-picking simplicity, higher order-picking accuracy, and improved employees' well-being– demonstrate the potential for AI-based new technologies to improve warehouse operations (Mahroof 2019; Ali et al. 2023; Cano et al. 2023; Pasparakis et al. 2023). The benefits identified in this study can transform the warehousing process through operational refinement and help overcome a set of common logistical challenges faced in the supply chain networks utilizing data-driven optimization (Turienzo et al. 2024). Among these benefits, travel distance and time reduction were further examined using a quantitative approach.

Although time reduction was non-significant, it can be inferred that time could be estimated in relation to the distance and speed. This non-significant time reduction result does not undermine the outcome because reductions in distance can eventually contribute to time savings with the help of other improvements. The findings on *reductions in travel distance and travel time* suggest that the order-picking efficiency can be improved by AI-based batching optimization. These findings align with prior research emphasizing the importance of order batching and using AI to enhance picking efficiency (Kuhn et al. 2021; Cergibozan and Tasan 2022; Zhou et al. 2023).

The qualitative results highlighted additional benefits not captured through quantitative measurements. This study suggests that certain advantages contributed to the development of other benefits. In addition to routing optimization, improved documentation emerged as a significant benefit, leading to reduced paperwork complexity and volume. The combined effects of improved documentation and reduced travel distance/time, achieved through batching, helped to increase the simplicity of order picking and enhanced employee well-being. As a result of more efficient routing, simplified picking processes, improved documentation, and enhanced employee well-being, picking accuracy increased, and errors decreased. Furthermore, the reduction in time, distance, and paperwork, alongside improved picking accuracy, had positive environmental implications. Paper usage decreased, and machines or trucks were utilized less frequently, leading to lower fuel consumption and longer machines lifetime. Finally, costs were reduced due to decreased energy consumption from reduced truck travel, lower truck maintenance from extended machine lifetime, decreased labor costs due to faster completion, and reduced stationary costs with less paperwork. Hence, it can be argued that these benefits are interrelated, aligning with previous literature (see, for example, Frederico et al. 2020; Dolatabad et al. 2022; Cano et al. 2023).

From a TOE theory perspective, it is evident that all AI-based system-derived benefits generally target both internal and external environments due to their interconnected nature, where one benefit can play a key role in the creation of another (Schwaeke et al.. 2025). However, in terms of the direct impact, cost reduction, improved documentation, higher order-picking simplicity, and enhanced employee well-being are primarily internal benefits because they largely affect the inside of the warehouse. These benefits focus on improving internal processes, reducing costs, and enhancing working conditions within the warehouse. Conversely, the positive environmental impact primarily pertains to the external context. This benefit aligns with overall sustainability goals and potential compliance with environmental laws and regulations established by governing bodies, and it highlights the broader external implications and consequences of AI-based systems. For benefits such as reduced travel distance and time, along with higher order-picking accuracy, it can be affirmed that these have effects in both the internal and external contexts. Internally, these benefits positively impact picking activity, performance, and efficiency within the warehouse. Simultaneously, they enhance the external context by enabling more reliable and higher-quality customer service.

In the TOE theory, the technological context refers to the characteristics and attributes of the technology itself (Wang et al. 2010; Abed 2020). For AI-based systems in Sienzi operations, the technological context includes elements such as the perceived benefits that the system brings to the warehouse. Leveraging AI advancements provides the warehouse with a range of benefits that positively impact various aspects of its operations (Turienzo et al. 2024). These benefits include cost reduction, improved documentation, enhanced employee well-being, reduced travel distance and time, simpler and more accurate order picking, and positive environmental impacts. In this case, all these benefits are made possible by advancements in AI technology. These findings align with Sodiya et al. (2024) regarding AI's role in warehouse automation.

6.2 Critical success factors and challenges

It is important to note that identified challenges in this study can be considered as critical success factors in the broader context of AI technology adoption (Marchet et al. 2015; Lee et al. 2018; Custodio and Machado 2020; Peng et al. 2021). If these challenges are effectively addressed, they can substantially enhance the opportunity to achieve the targeted outcome driven by the AI-based system. Challenges are a set of critical success factors that have faced complications throughout the process. Thus, we propose that strategic alignment, structural alignment, operational alignment, data privacy, technology usability, costs considerations, and degree of resistance or willingness to change are all critical success factors. However, strategic, structural, and operational alignments have faced specific barriers within their subsets. These barriers, along with cost considerations and resistance to change, account for challenges that have hindered the path toward optimal utilization of the AI-based system.

This study provided strong evidence for the critical role of strategic alignment in AI-based system adoption, particularly through strategic fit, functional integration, and business process re-engineering. Strategic fit centers on the implications of IT strategy for business strategy (Henderson and Venkatraman 1999) demonstrating, in our case, a reliable match between what the warehouse demanded from such an adoption and what the technology has delivered. The AI-based system successfully aligned with the warehouse's broader strategic goals. This alignment illustrates how technology's capabilities reinforce strategic objectives, which is particularly evident in the improvements related to order=picking efficiency and accuracy, as discussed previously. However, functional integration encountered notable complications. Functional integration refers to maintaining coherence between technology's capability and the organizational setting (Henderson and Venkatraman 1999). In our case, the batching capability enabled by the AI-based system combined with Sienzi's traditional labeling approach underpinned the incoherence between two closely connected activities of the warehousing process: picking and sorting. This incoherence was resolved when Sienzi adjusted its labeling approach.

In this paper, we associate such incoherence with four elements that hindered the functional integration:

1. Poor pre-implementation review of the business/warehouse landscape, which led to an incomplete picture of the internal operations and processes within the warehouse. Conducting such a review could have identified the upcoming sorting problem and, hence, helped to prevent it.
2. Lack of joint planning involving both Kairos and Sienzi: joint planning would enable the warehouse team to better understand the impact of the AI-based system, clarify expectations in advance, and elaborate on the specificities of its activities. This process could have potentially highlighted upcoming sorting issues. On the other hand, Kairos could propose possible technological solutions to prevent such an outcome.

3. Lack of robust communication: Achieving functional integration (i.e., strategic alignment) requires extensive communication, which was largely overlooked.
4. Limited understanding of Kairos regarding the operational dynamics of Sienzi: as a technological solution provider, it is incumbent on Kairos to have an astute comprehension of the operations in the hosting environment. A deeper understanding of Sienzi's operations could have been beneficial in avoiding such complications.

Moving on to the next point, structural alignment involves achieving architectural integration (Peng et al. 2021), which in our case refers to the alignment between the architectures of the warehouse's existing technologies and the AI-based system, particularly in terms of technological interoperability. In this study, such interoperability was a key goal, specifically between the AI-based system and the warehouse's ERP system. Without interoperability and the establishment of the API linking them, the AI-based system would have been unable to deliver the promised performance. To address this need, communication between Kairos and Select became vital for developing a suitable API to establish the required connection between the technologies. However, due to internal challenges within Select, direct technical communication between these two actors was lacking, resulting in delays in achieving integration.

Communication also plays a crucial role in operational alignment. This type of alignment centers on the coordinated flow of operations to achieve success (Maes et al. 2000; Peng et al. 2021), which refers to maximum utilization of the AI-based system for Sienzi's picking activity. To achieve operational alignment, effective communication and collaboration are essential between Sienzi, Kairos, and Select. In addition, technological maintenance is critical for sustaining operational alignment over time. The results indicate difficulties in understanding the new checklist generated by the AI-based system, highlighting a challenge stemming from changes in the documentation approach. This was revealed because the new checklists differed in format from Sienzi's traditional checklists. To address this challenge, the triadic collaboration of Kairos, Sienzi, and Select was instrumental in providing the necessary training and education to help the pickers to successfully read and understand the new checklists.

In general, technology-business alignment focuses on sustaining a symbiotic relationship between business and technology to generate competitive benefits (Duffy 2002, as cited in De Haes and Van Grembergen 2009). It is marked in the literature as important in achieving business goals (Luftman 2004; Alaeddini et al. 2017), and this paper is in line with previous literature on the importance of alignment. In addition, Peng et al.'s (2021) categorization of alignment into strategic, operational, and structural elements aligns well with the empirical evidence of this research. An important component of alignment is communication (Maes et al. 2000; Luftman 2004). In our case, communication was a crucial factor in all three strategic, structural, and operational alignments. This supports Luftman et al. (1999), who state that all alignment elements are important, but none of them matter if effective communication is absent. In the case of structural and strategic alignment, communication has been impaired, leading to the emergence of challenges. However, to achieve operational alignment, proper communication helped in overcoming the relevant challenge.

Data privacy is the next critical success factor (Szozda 2017; Luthra and Mangla 2018; Sodiya et al. 2024). In this case, no issues related to data privacy were identified. This may be due to three data privacy concerns addressed by the actors involved. First, permission was obtained from the parties involved to share the generated data, and it appears that an established mechanism was in place for this purpose. Second, a confidentiality agreement was approved by partners, and a non-disclosure agreement (NDA) was signed. Third, privacy matters were managed in accordance with established regulations and laws.

A specific challenge concerned the issue of costs. Analysis and discussion of benefits revealed how the AI-based system contributed to cost reduction. Nevertheless, results indicate that certain costs arise, related to warehouse expenses, which can offset the cost savings achieved. First, using the AI-based system incurs subscription fees, which Sienzi must bear in addition to the implementation fee. For continuous use of the AI-based system, Sienzi has to pay a monthly subscription fee. Second, the warehouse incurs costs associated with adapting its operations to maximize the system's benefits. These results highlight the importance of balancing initial and setup costs with achieved cost savings to create a cost-effective warehouse management strategy (Kalkha et al. 2024). As previously discussed, simulation results indicate that adding an extra tunnel in the warehouse can lead to a further reduction of 13.91% in travel distance. However, this tunnel was not implemented due to the additional costs and potential economic loss involved in configuring such a layout.

Another challenge noted in this study is resistance to change. Throughout the project, instances of resistance emerged regarding both the tunnel construction and the new approach of fully instructed routing. The resistance to the former arose from employee fatigue due to heavy workloads, making them reluctant to embrace change in their daily work routine. The resistance to the latter stemmed from an initial perception that the instructed routing approach limited their freedom in the picking process. Similarly, the previous literature has emphasized the impact of socio-technical factors on resistance to change (Hagström et al. 2023).

Finally, *managerial commitment* was identified as another critical success factor in this study. Management commitment is an important element that can significantly contribute to change management (Kumar et al. 2021). In this case, a firm commitment from Sienzi's management to undergo technological and process transformations in their warehouse was observed. Therefore, this element is not regarded as a challenge. However, in the case of tunnel construction, a more robust commitment might have motivated the management to conduct an inquiry. Such inquiry could have focused on identifying a suitable approach to construction, optimizing space utilization, and analyzing associated costs and benefits from both short- and long-term perspectives before deciding against building the tunnel.

From the perspective of TOE theory, strategic, operational, and structural alignments address both internal and external contexts due to the involvement of at least two parties. These alignments also target the technological context. Specifically, strategic alignment includes technological attributes that support business strategies, operational alignment involves elements such as technological maintenance, and structural alignment focuses on the interoperability of technologies, highlighting their technological characteristics.

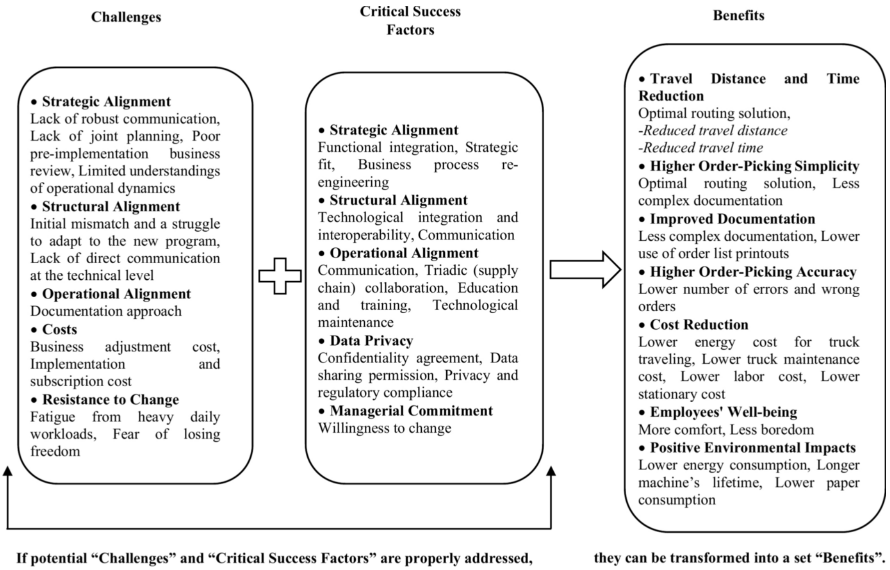

Fig. 2 Summary of the qualitative and quantitative analyse

Data privacy spans the internal, external, and technological contexts. Since data flow is inherent to the AI-based system, its relevant privacy considerations extend beyond the boundaries of a single party. Adjustment costs are specific to the internal context, depending on the unique characteristics of the warehouse. Implementation and subscription costs extend from the internal context into the external context. This is because the implementation and subscription costs require engagement with an external party—the AI-based system provider—and depend on its pricing model to provide the technology. While some costs relate to fees for utilizing the technology, they do not directly stem from the technology itself, placing them outside the technological context. Resistance to change also relates to the internal context because it mainly centers on the internal situation of the warehouse. Moreover, resistance to change relates to the technological context due to socio-technical motivators of resistance. Lastly, managerial commitment is relevant to the internal context. The main findings of the study discussed in this section are summarized in Fig. 2.

By categorizing the challenges and critical success factors into technological, internal, and external contexts, these findings align with the TOE theory framework, illustrating how various factors impact the adoption and effective use of the AI-based system in Sienzi.

7 Implications for literature and theory

The findings of this study provide empirically driven insights into the positive impact of the AI-based system on the warehousing process, as well as associated challenges and critical success factors. These insights can offer valuable contributions to research efforts, addressing the common case of AI projects' failure or underperformance (see

Rayome 2019; Zhang et al. 2021). This contribution is further amplified by the dearth of research on AI use cases in the warehousing context (Mahroof 2019; Custodio and Machado 2020).

Furthermore, the study clusters the benefits, challenges, and critical success factors into internal, external, and technological contexts, consistent with the TOE framework. This clustering helps identify the contextual elements influencing decisions related to technological adoption and usage (see, for example, Ali et al. 2024). By drawing on the TOE framework, the study builds on the existing theoretical foundation of this domain (see, for example, Baker 2012) and provides avenues for future research.

Additionally, by identifying the benefits, challenges, and the TOE contexts to which they correspond, this study supports the sensing component of dynamic capabilities theory. These identified themes contribute to forming the judgment necessary for the subsequent seizing component. Similarly, identifying the critical success factors and their corresponding contexts bolsters the transformation component because it effectively clarifies key elements for the alignment process.

Moreover, by employing both quantitative and qualitative methods, the study offers a comprehensive examination of the central elements involved in order-picking activity. The mixed-methods approach—integrating quantitative analysis with qualitative insights—strengthens the validity of the findings. This triangulated approach provides researchers with a broader and more precise understanding of the topic. Furthermore, the use of the Gioia method for qualitative analysis ensures more robust and reliable qualitative results, addressing potential criticisms related to data cherry picking in qualitative research.

Ultimately, this study emphasizes the importance of comprehensive technological investigations by tapping into the benefits, challenges, and critical success factors. This approach aims to avoid a fragmented body of literature in this area and promotes a more holistic understanding of the implications of the advanced technologies in the context of Industry 4.0 (see, Ali et al. 2024). As technologies grow increasingly complex and often overlap, the technological ramifications and implications need to be addressed robustly.

8 Practical implications

By examining the upsides, downsides, and critical success factors associated with AI technology in the warehousing context, this study has explored multiple facets of such projects, thereby facilitating more informed decision making for managers and practitioners. This, in turn, can improve their ability to manage the specific demands of similar technological adoptions and usages. The study's focus on the picking activity within the warehousing process is particularly significant because it represents one of the costliest operations in the relevant domain (Coyle et al. 1996; de Koster et al. 2007; Richards 2018). The insights gained from this research offer valuable guidance for warehouse managers seeking to optimize their picking operations and fully leverage the benefits of AI-based systems.

This study identified several benefits of using an AI-based system in the order-picking activities of a warehouse. Reducing the travel distance and travel time required for order picking is a vitally important outcome, given the costly nature of this activity. Additionally, implementing the AI-based system offers further benefits, such as a positive environmental impact and improved employee well-being. These additional benefits, although significant, are not always on the radar of adopters, as evidenced by the fact that they were neither anticipated nor explicitly targeted by the stakeholders involved.

Furthermore, adopting a new technology often requires alignment with organizational and structural changes. The alignment process can be accompanied by challenges that may hinder the technology's full potential, as indicated by the challenges identified in this study. In this regard, critical success factors, such as managerial support, can facilitate the alignment process, smoothing transitions and fostering a mindset of openness that helps overcome obstacles. These challenges and critical success factors may be somewhat generalizable to warehouses with characteristics similar to those described in the case study. If appropriately addressed by management, implementing AI in the warehouse can significantly enhance operational efficiency and improve overall performance.

9 Conclusion, limitations, and recommendations for future research avenues

Based on the analyses and discussions in this paper, seven benefits have been identified as a result of using the AI-based system in Sienzi. Among these benefits, one central dimension related to travel time and distance was quantitatively measured using two indicators. Both qualitative and quantitative findings indicate a positive impact of the system on this dimension, enhancing research validity by confirming results using multiple methods. Furthermore, it was observed that the benefits are interrelated, meaning that the emergence of certain benefits contributes to the development of other benefits.

Additionally, our findings identified challenges and critical success factors, which respectively hinder and facilitate the full exploitation of the AI-based system in the warehouse. It was noted that all identified challenges also serve as critical success factors, having encountered impediments throughout the process. Strategic, structural, and operational alignments fall into both critical success factors and challenges because certain subsets within these alignment types have been associated with complications. This places them not only among the facilitating themes but also, from specific sub-angles, among the hindering elements.

Moreover, while this study focuses on a single case in Türkiye, the findings may be generally applicable to the global warehousing industry for several reasons. First, the statistical evaluations of quantitative measures, particularly the significant reduction in distance ($p=0.001$) and the near-significant reduction in travel time ($p=0.056$), demonstrate robust and reliable results. These findings suggest that the observed effects are not due to random variation, which enhances the study's replicability. Replicability is foundational for generalizability because consistent and reliable results are prerequisites for applying findings to broader contexts. Additionally, the detailed information on key actors in this technological transition, as well as details of the interviews, such as durations and interviewees' positions, provides a foundation for comparisons in future studies. The use of the Gioia approach offers transparency in transforming raw interview data into final themes, which can be used for comparative purposes in future research. These factors enhance the relevance and applicability of this study's findings to other research settings with similar characteristics.

Although this study provides valuable insights into the adoption of AI-based systems in warehouses, several limitations should be acknowledged, and potential avenues for future investigation proposed. First, the empirical setup of this paper focuses on a single case study, which may limit the generalizability of the findings to other contexts despite the statistical significance of the quantitative results, Gioia approach, and triangulation design used in the methodology. To increase the robustness and applicability of the results, future research should aim to incorporate case studies from different industries and regions, thereby establishing a stronger foundation for validating the findings and broadening the applicability of the study's findings.

Second, this paper focuses on a technological system driven by AI and supplemented by cloud and simulation technologies to optimize routes in order-picking activity. Future research could benefit from exploring other warehousing technologies that can enhance picking activities, laying the foundation for a more robust body of literature in this area.

Third, the specific context of Sienzi and its predominantly Turkish workforce could influence the emergence of certain themes. For instance, the critical success factor of data privacy may be associated with different outcomes when involving other actors from different locations. Similarly, the challenge of resistance to change may vary in cases with different socio-economic characteristics. Consequently, future research could explore similar setups in different geographical locations and with diverse employee demographics to determine the cross-cultural implications of the identified benefits, challenges, and critical success factors.

Finally, this study was limited to a quantitative examination of travel distance and time, excluding other benefits, challenges, and critical success factors from quantitative assessment. Moreover, the findings from the qualitative study suggest that benefits, challenges, and critical success factors are related to each other. Therefore, future research could expand the quantitative analysis to include a broader range of dimensions in order to gain a more comprehensive understanding of their impact on warehouse operations.

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