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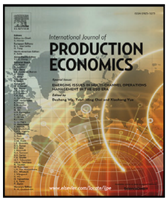

Side by Side or “Get Out of My Way!”—Examining the Impact of Picker Blocking and AGV Assistance in Picker-to-Parts Order-Picking Systems

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ABSTRACT

Manual order picking remains a labour- and cost-intensive warehouse process. Automation technologies have gained traction, with automated guided vehicles (AGVs) assisting human pickers by handling transport tasks and optimising workflows. However, due to high cost levels and infrastructural constraints, AGVs are often introduced incrementally, resulting in mixed-technology scenarios in which workers with a prior-generation technology and workers with the new (AGV) generation technology operate side by side, for example, in the same warehouse aisle. One challenge in such settings is picker blocking, which occurs when the actions of one picker impede or delay the movements of another. This study empirically examines pick-column blocking and within-aisle blocking with respect to their impact on task performance time. Using a mixed-effects regression model, we analyse 490,398 pick events from a German retailer during 2023. This approach accounts for repeated observations and individual heterogeneity in picker performance over time. Our results show that both types of blocking significantly increase task performance time. AGV assistance mitigates these negative effects, reducing the additional delay by 3.4% for pick-column blocking and 2.1% for within-aisle blocking. Our results demonstrate that AGVs do more than provide transport assistance, reducing congestion and ensuring smoother, more efficient movement. The study provides valuable theoretical and management insights to optimise warehouse operations and contributes to the growing literature on human–AGV collaboration in logistics.

1. Introduction

Manual order picking remains a central operation in many warehouses and distribution centres, with human pickers retrieving products from storage locations to fulfil customer orders (Cordeau et al., 2025). This process is widely recognised as one of the most labour-intensive, time-consuming, and costly warehouse operations, accounting for a substantial share of total operating costs (Richards, 2018; Perotti et al., 2025). Despite the growing interest in automation, manual picker-to-parts systems continue to dominate in many industries. This is particularly the case in retail warehouses handling high-volume, low-mix orders (Grosse, 2024; Loske, 2022), due to the ability of human pickers to handle complex and variable tasks, and adapt to unexpected changes, functionalities that fully automated systems cannot yet provide (Richards, 2018; Vanheusden et al., 2022). In the context of growing e-commerce demand, labour shortages, and heightened competition, warehouse managers are increasingly exploring ways to enhance order-picking performance and productivity, for example, through supportive technologies such as automated guided vehicles (AGVs) (Grosse, 2024).

AGVs have emerged as a promising way to augment manual operations (Kopp et al., 2023). These vehicles autonomously follow human order pickers through warehouse aisles, assuming transportation tasks to improve performance and streamline operations (Pasparakis et al., 2021). By automating repetitive movements, AGVs enable human pickers to focus on the primary task of retrieving products (Tutam and de Koster, 2024). However, rather than entirely replacing manual operations, AGVs are often introduced incrementally due to the high costs and infrastructural adjustments required for full fleet implementation (Koreis et al., 2025a). This phased adoption leads to transition scenarios, where prior and new (AGV) generations of technology coexist within a warehouse workspace. In these scenarios, workers may use either (old) manually steered industrial trucks or (new) AGVs to perform order picking tasks. This operational setup reflects the economic and practical realities of modern warehouses, in which a

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complete transition to AGV fleets or full automation is not immediately feasible (Loske, 2022).

For efficient integration of AGVs into existing warehouse environments, it is essential to consider the operational challenges that arise when prior and new (AGV) generations of technology (as supportive technologies for human order pickers) coexist (Rainer et al., 2025). One such challenge is picker blocking, where one picker's actions impede or delay the picking process of others (Winkelhaus et al., 2022). Picker blocking is a common challenge in warehouse environments, particularly in narrow-aisle systems with limited space (Franzke et al., 2017). It often results from high pick density (Koreis et al., 2025b), inefficient routing (Prunet et al., 2025), or suboptimal storage assignment (Baals et al., 2025) and leads to increased times for task performance (Hong et al., 2012). These challenges are amplified in high-density warehouses, where congestion and delays are more frequent (Koreis et al., 2025b).

The effects of picker blocking have been extensively examined, with studies highlighting its adverse impact on warehouse throughput and task performance time (Elbert et al., 2015a; Franzke et al., 2017; Löffler et al., 2021). The literature has largely focused on manual order-picking systems, analysing factors such as aisle design, storage assignment policies, and routing strategies as key determinants of congestion (Bahrami et al., 2017; Franzke et al., 2017; Hong et al., 2012; Pan and Wu, 2012). While these studies provide valuable insights into how blocking effects can be mitigated, they primarily address traditional manual setups without technological assistance. More recent studies have investigated order-picking systems, where robots operate alongside human pickers. These reveal that supportive technology can influence congestion dynamics in both positive and negative ways (Koreis et al., 2025b; Winkelhaus et al., 2022). Winkelhaus et al. (2022) find that the degree of automation significantly influences congestion patterns in hybrid order-picking systems. Specifically, autonomous robots can effectively reduce human-to-human blocking when movement is properly coordinated. The findings further indicate that robot-induced delays may occur if paths are not optimised, demonstrating that, depending on the operational context, automation can both mitigate and exacerbate congestion. Koreis et al. (2025b) empirically analyse the impact on picker blocking of system-level robot share—that is, the proportion of pickers operating with an AGV in the same aisle. The results indicate that moderate AGV integration (below 20% of total pickers using an AGV) helps distribute workloads and reduce in-aisle blocking, particularly when two to five pickers operate in the same aisle, whereas excessive AGV density can create bottlenecks due to rigid movement patterns, especially in high-density settings.

Empirical evidence on the extent to which robotic assistance mitigates picker blocking remains limited, however. While prior research has focused on system-level outcomes, such as overall AGV share or aggregate throughput (Koreis et al., 2025b; Winkelhaus et al., 2022), little is known about how human–AGV collaboration affects picker-level congestion phenomena, specifically pick-column and within-aisle blocking, and how these influence individual task performance time. Previous studies have also largely overlooked human-centric operational factors, such as spatial perception, perceived safety, and adaptive behaviour, which can significantly shape congestion dynamics in shared workspaces. The present study addresses these gaps by empirically analysing picker-level blocking in a real-world warehouse, quantifying the mitigating effects of AGV assistance, and incorporating human behavioural aspects to provide insights into how supportive technologies interact with humans at the operational level.

Our study seeks to address this gap by empirically examining the relationship between picker blocking and task performance time in warehouse environments where both prior and new (AGV) technology generations coexist to support of human order pickers. First, we analyse the overall impact of pick-column blocking and within-aisle blocking on task performance time, specifically how these congestion effects influence average picker performance. Second, we investigate whether AGV assistance affects the extent to which picker blocking impacts task performance time. Our study provides insights into whether AGV implementation improves order-picking performance by alleviating congestion-related delays.

This paper aims to answer the following two research questions:

- **RQ_1**: *To what extent do pick-column blocking and within-aisle blocking impact average task performance time in high-volume low-mix retail picker-to-parts order-picking systems featuring prior- and new-generation technologies?*
- **RQ_2**: *To what extent does AGV assistance impact pick-column blocking and within-aisle blocking in high-volume low-mix retail picker-to-parts order-picking systems?*

We answer these research questions using a highly detailed archival order-picking dataset from a warehouse of a German brick-and-mortar retailer. The dataset comprises 490,398 individual pick events, performed by AGV-assisted and manually operated order pickers in a shared aisle workspace from 1 February 2023 to 30 September 2023. We employ a mixed-effects regression model to analyse the impact of picker blocking on task performance time and assess how AGV assistance impacts pick-column blocking and within-aisle blocking. This methodological approach accounts for within- and between-individual variations, allowing us to isolate the effects of picker blocking while considering individual differences among pickers.

Our paper makes a number of important contributions. The study provides empirical evidence of how congestion dynamics influence task performance in hybrid order-picking systems where humans operating with prior technology and AGV-assisted pickers operate simultaneously. By distinguishing between pick-column blocking and within-aisle blocking, the study quantifies how different types of congestion impact task performance time and identifies the specific operational conditions under which AGV assistance mitigates these effects. The results reveal that AGV assistance reduces congestion-related delays by 3.4% for pick-column blocking and 2.1% for within-aisle blocking, indicating that automation can enhance workflow continuity and coordination even in partially automated environments. Beyond this empirical contribution, the study links the performance improvements identified to managerial decision-making by translating them into economic outcomes through a return-on-investment (ROI) analysis, thereby providing actionable guidance for the targeted deployment of AGVs in high-congestion zones. In addition, the findings enrich the theoretical understanding of human–AGV collaboration by connecting behavioural mechanisms in shared workspaces to expectancy violations theory (EVT) and interpersonal distance (IPD). The findings suggest that predictable patterns of AGV movement lower expectancy violations and perceived interpersonal distance, which helps minimise hesitation and brief disruptions in congested aisles. Together, these contributions advance the theoretical and managerial discourse on partial automation in warehouse operations and offer a foundation for future research on human–AGV collaboration in shared industrial environments.

The remainder of this paper is structured as follows. Section 2 contains a review of the relevant literature, while Section 3 focuses on methodology, including the empirical order-picking setting and data-collection process. Section 4 outlines the relevant operational variables and the econometric framework. Section 5 then presents the empirical results. In Section 6, we discuss our findings directed at theory and management learnings, draw conclusions, and offer an outlook on future relevant research.

2. Related work

As regards related and relevant literature, we begin by examining key factors influencing order-picking performance, including warehouse layout, storage assignment, routing policies, and order batching.

We then consider research on picker blocking in warehouse operations, highlighting its causes, impacts, and proposed mitigation strategies. Our focus then shifts towards AGV-assisted travelling in order picking, investigating how AGVs impact picker movements and performance. We pay particular attention to technical aspects and human–AGV collaboration from other theoretical perspectives embedded in, for example, psychology and theories of human resource (HR) management. Finally, we summarise the insights from the literature and position our study within this context, identifying the knowledge gaps our research aims to address with a problem-based theory discussion perspective (Bendoly and Oliva, 2025).

2.1. Warehouse design and order-picking performance

Researchers have explored various factors affecting order-picking performance, including warehouse layout (Henn et al., 2013; Roodbergen and Vis, 2006), storage assignment (Baals et al., 2025; Calzavara et al., 2019), routing policies (Prunet et al., 2025; Masae et al., 2020), and order batching (Bozer and Kile, 2008; Matusiak et al., 2017).

Warehouse-layout planning is foundational, as it dictates the configuration of the warehouse, including the number and arrangement of aisles and cross aisles (Hsieh and Tsai, 2006). Standard layouts, such as rectangular arrangements, are common, but alternatives like U-shaped layouts and fishbone layouts have been proposed to optimise picker travel distance and minimise congestion (Henn et al., 2013; Pohl et al., 2011; Roodbergen and Vis, 2006). Optimised design choices affect performance by minimising travel and by influencing instantaneous picker density, co-location at popular slots, and the probability of simultaneous aisle use, which are proximal drivers of blocking and thus influence task performance time. While alternative warehouse layouts reduce average travel, they can also funnel traffic into the same cross-aisle junctions and high-demand corridors, increasing short-term occupancy and the likelihood of within-aisle blocking if picker arrival processes become synchronised (Henn et al., 2013; Roodbergen and Vis, 2006).

Storage-assignment rules significantly influence picking performance by determining how products are allocated to pick locations (Calzavara et al., 2019). With class-based storage, for instance, products are categorised based on their turnover rates and those with high turnover are strategically located closer to the depot or pick-up/drop-off points to reduce travel time (Rao and Adil, 2013). Other methods, such as random storage or turnover-based assignment, also have implications for order-picking performance (Pohl et al., 2011). Prior research has shown that aligning picking sequences in warehouses with store-specific layouts can reduce picker travel distance and effort (Baals et al., 2025). Demand-driven storage-allocation strategies that forecast item demand and optimise storage placement can further enhance order-picking performance by reducing travel distances and improving picker performance (Ho et al., 2025). However, concentrating high-demand products near the depot can create traffic hotspots, where multiple pickers frequently access adjacent pick locations (Pohl et al., 2011; Calzavara et al., 2019). Such hotspots increase the likelihood of pick-column blocking events (Franzke et al., 2017), which, in turn, prolong task performance (Bahrami et al., 2017; Chen et al., 2013).

Routing policies, which govern which paths pickers take through the warehouse, are crucial for minimising travel distance and avoiding congestion (Masae et al., 2020). Heuristic strategies, such as S-shaped, return routing, and U-shaped routing, are widely used due to their simplicity. In S-shaped routing, pickers traverse an entire aisle, reducing backtracking, while return routing limits aisle travel by having pickers exit from the same end (Rao and Adil, 2013). U-shaped routing, by contrast, allows pickers to enter an aisle, retrieve products from both sides, and exit at the same end, often optimising travel for clustered picks (Glock and Grosse, 2012). Recent research has demonstrated that solving the picker routing problem in such settings is NP-hard, underscoring the difficulty of optimising paths when multiple decision variables, such as cross-aisle usage and order distribution, are involved (Prunet et al., 2025). While optimal routing can minimise travel distance, it also synchronises picker movements and may increase the likelihood of simultaneous arrivals in particular aisle segments, amplifying blocking-related delays if picker density is high (Gue et al., 2006). Conversely, routing that deliberately de-synchronises flows or exploits cross-aisle dispersion may slightly increase travel but reduce blocking-induced idle time, yielding net performance gains when congestion externalities dominate (Rao and Adil, 2013; Glock and Grosse, 2012).

Finally, order batching, combining multiple orders into a single picking task, has been studied for its potential to improve capacity utilisation (Grosse et al., 2014). By grouping orders efficiently, batching reduces overall travel distance and enhances order-picking performance, leading to increased throughput and better resource utilisation. Data-driven approaches optimise order batching by accounting for factors such as system congestion and human behaviour, ensuring more robust and adaptable solutions in dynamic warehouse environments (Bayram et al., 2022). However, large batch sizes can result in prolonged occupation of pick locations and extended handling times, increasing the waiting time for following pickers and negatively impacting overall task performance time despite fewer travel legs (Bahrami et al., 2017).

The performance of warehouse operations depends on the seamless integration of layout design, storage assignment, routing policies, and order batching. While these factors aim to optimise travel distances and improve throughput, they can also introduce operational challenges when multiple pickers are navigating the same workspace. In high-density environments, particularly those with narrow aisles and clustered pick locations, picker blocking becomes a critical issue, disrupting the intended performance gains of optimised order-picking strategies (Franzke et al., 2017). This phenomenon occurs when pickers obstruct each other's paths, leading to delays, longer task performance times, and reduced system performance (Bahrami et al., 2017; Chen et al., 2013).

Recent research highlights that these planning problems are highly interdependent and should be solved in an integrated manner rather than sequentially. For instance, policies that minimise travel distance can unintentionally increase picker density in high-turnover zones, thereby raising the probability of blocking and waiting times. van Gils et al. (2017a, 2019) demonstrate that jointly optimising order batching, routing, and picker scheduling can reduce total task performance time by up to 17% in a real-life warehouse. In addition, their state-of-the-art review shows that integrating storage, batching, zoning, and routing decisions yields superior overall performance and creates more robust systems under real-life constraints, for example, safety requirements and picker blocking (van Gils et al., 2017b). These findings underline the importance of considering planning problems simultaneously, as only an integrated approach can balance the minimisation of travel distance and the risk of congestion. Consequently, it is essential to understand the causes and consequences of picker blocking not just as a local phenomenon but as a system-level effect of warehouse design and planning decisions.

2.2. Picker blocking in warehousing

Picker blocking occurs when order pickers obstruct one another's movement, leading to increased waiting times, inefficient routing, and reduced overall warehouse throughput (van Gils et al., 2018). Various studies have categorised picker blocking based on the nature of the obstruction and the warehouse layout.

Picker blocking is generally classified into two main types: in-the-aisle blocking and pick-column blocking (Parikh and Meller, 2009). In-the-aisle blocking occurs in narrow-aisle warehouses where pickers cannot pass each other within the aisle. This often results in one picker having to wait for another to exit before proceeding (Gue et al., 2006). Pick-column blocking happens when multiple pickers attempt to retrieve products from the same pick location simultaneously. This form of blocking can occur in narrow- and wide-aisle warehouses, making it a critical concern regardless of warehouse layout (Franzke et al., 2017). Refinements of these classifications include total aisle blocking, where an entire aisle becomes inaccessible due to congestion, and within-aisle blocking, where the type of interaction between pickers (manual or robot) influences congestion patterns (Winkelhaus et al., 2022).

Several studies have examined the causes and implications of picker blocking. Storage assignment policies and routing strategies have been shown to significantly influence the likelihood of picker blocking (Chen et al., 2013; Franzke et al., 2017; Löffler et al., 2021). For instance, class-based storage assignment, with high-turnover products placed closer to the depot, can lead to increased congestion in high-demand areas, exacerbating blocking incidents (Pan et al., 2012). Routing policies also play a crucial role in mitigating picker blocking. S-shaped routing, common in order picking, can reduce blocking frequency by ensuring that pickers move through the warehouse efficiently (Hong et al., 2012). However, return routing and mid-point routing strategies have been studied for their potential to alleviate congestion by redistributing picker traffic more evenly (Franzke et al., 2017).

Agent-based simulation techniques have been more broadly employed to quantify the impact of blocking on warehouse performance. Franzke et al. (2017) demonstrated that picker blocking can significantly increase travel and idle times, reducing system efficiency. In their extensive simulation analysis (Bahrami et al., 2017) evaluate the impact of order batching, routing policies, and storage assignments on picker congestion. Their results indicate that routing strategies, particularly return routing, significantly influence the frequency of picker blocking, and class-based storage can intensify congestion in high-demand areas. Similarly, Elbert et al. (2015b) employ an agent-based simulation to investigate the effects of picker blocking in manual order-picking systems with different routing-policy combinations. The study focused on a rectangular warehouse with narrow aisles and three order pickers operating simultaneously. The results revealed that the combination of ‘largest gap’ routing for two pickers and a ‘combined’ routing policy for the third picker resulted in the lowest mean throughput time, effectively reducing the impact of picker blocking. Return routing performed the worst, with the frequent aisle re-entry leading to the highest level of congestion.

Congestion effects and strategies to mitigate picker blocking have been extensively examined with respect to manual order picking, but the increased automation of warehouse operations introduces new dynamics that must be considered. As warehouses transition, hybrid environments where human pickers and autonomous robots operate together new congestion patterns emerge, creating both challenges and opportunities.

The interaction between human pickers and AGVs in hybrid order-picking environments introduces layers of complexity. Spatial and temporal coordination is required, as pickers and AGVs operate in the same workspace and must maintain predefined safety distances. AGVs follow the picker, stop when the picker stops to retrieve an item, and resume movement when the task is completed (Tutam and de Koster, 2024). This behaviour can create temporary blockages if multiple pickers are operating in close proximity; AGVs may queue behind one another or wait for a clear path before proceeding. Moreover, the constant following distance enforced by the AGV can limit overtaking possibilities and amplify within-aisle blocking in high-density situations.

From a managerial perspective, hybrid environments also differ from purely manual settings in a psychological sense. Workers must adapt to the predictable but rigid movement of AGVs and this may initially lead to hesitation or increase their cognitive load (Jacob et al., 2023; Hosseini et al., 2024). There is also empirical evidence that divergence in the perspectives of management and operational staff on AGV implementation can impede worker acceptance. There is clear need for effective organisational change management and perspective-taking by project leaders (Kopp et al., 2023). Human–AGV dynamics can increase waiting times, alter picking sequences, and intensify congestion as a result. Consequently, routing strategies and human–robot coordination protocols must be carefully designed to minimise blocking effects, as we elaborate in Section 2.3.

These observations are consistent with prior simulation studies. Winkelhaus et al. (2022) emphasised that the degree of automation significantly influences congestion patterns, with autonomous robots reducing human-to-human blocking but potentially increasing robot-induced delays if their paths are not optimised. The agent-based simulation study found that in a hybrid order-picking system, automation technology can mitigate picker blocking when properly coordinated but can also introduce new congestion challenges if the movement of humans and robots is not effectively synchronised.

Koreis et al. (2025b) empirically analysed the impact on picker blocking of system-level robot share (the proportion of pickers operating with an AGV in the same aisle) in different warehouse configurations. They found that moderate AGV integration (below 20% of total pickers using an AGV) helps distribute workloads and reduce in-aisle blocking, particularly when 2 to 5 pickers operate in the same aisle. When AGV density exceeds this threshold, their rigid movement patterns might create a bottleneck, especially in high-density settings.

Overall, picker blocking remains a key challenge in warehouse management. Various operational policies have been proposed to mitigate its effects, the growing adoption of automation technologies, such as AGVs and collaborative robots, introduces dynamics that fundamentally change congestion patterns. These are analysed further in Section 2.3.

2.3. *AGV-assisted travelling in order picking*

AGVs are used in warehouse order picking to reduce manual transport efforts by assisting human pickers to move products efficiently (Löffler et al., 2021). In picker-to-parts order-picking systems, AGVs typically follow human workers. This allows them to focus on retrieval tasks rather than transporting picked products to the next location (Pasparakis et al., 2021). These systems are increasingly implemented in the warehouses of high-volume, low-mix retail operations, where full automation or having a complete AGV fleet is not yet feasible due to economic and infrastructure constraints (Koreis et al., 2025a).

There are various operational models for integrating AGVs into order-picking systems. One of the most common is ‘order picker walks, AGV follows’, in which the AGV trails behind the human picker, carrying picked products (Tutam and de Koster, 2024). This setup reduces non-value-adding walking time and minimises the delays associated with mounting and dismounting industrial trucks (Koreis, 2025). Another option is ‘AGV leads, picker follows’, where AGVs guide human workers along optimised picking routes, potentially reducing congestion and improving navigation efficiency (Pasparakis et al., 2021).

Ensuring safe human–AGV collaboration is fundamental to the successful implementation of AGV technology in warehouse environments (Yingbo et al., 2025). Given that AGVs share the workspace with human workers, their safe and efficient integration into order picking workflows requires strict adherence to internationally recognised safety standards and consideration of human-centred factors such as perceived workload (Berti et al., 2025; Kumar et al., 2023). There has been increasing academic interest in the complexity of human–AGV interaction, with a particular focus on how automated systems impact worker performance and safety in collaborative environments (Tubis et al., 2024). Integrating real-time location tracking and wireless communication networks improves AGV coordination, prevents bottlenecks and improves overall system reliability (Szász and Csiki, 2025).

The ISO 3691-4:2020 safety standard for driverless industrial trucks outlines measures to regulate AGV behaviour in dynamic and unpredictable environments (DIN, 2020). One of the most crucial safety mechanisms is the emergency stop function. This ensures AGVs instantly interrupt movement in response to unforeseen obstacles and, in so doing, significantly reduces the likelihood of collisions (Rozhok et al., 2023). This feature is particularly vital in high-density warehouses, where sudden human movements or misplaced inventory can create unexpected hazards.

Collision avoidance systems also play a central role in AGV safety. These systems rely on advanced sensor technology to continuously scan the AGV's surroundings, detect obstacles, and adjust movement accordingly (Yingbo et al., 2025). Modern AGVs are operated through dynamic path-planning algorithms, enabling them to reroute in real time when they encounter unexpected obstructions; operational efficiency is maintained while minimising risks to human workers (Kubasakova et al., 2024).

Another key safety feature is adaptive speed control, which ensures that AGVs adjust their velocity based on environmental factors such as proximity to human workers, congestion levels, and the urgency of the task (Dabrowska et al., 2021). By dynamically regulating speed, AGVs can move efficiently while maintaining safe operating distances. In areas with high levels of human activity, AGVs automatically slow down or come to a complete stop, whereas in less congested zones, they can operate at higher speeds to optimise transport times. This flexibility is crucial for maintaining safety and workflow efficiency.

Such technology solutions are closely connected to human concepts and perceptions of safety, distance and space. The following section complements the operations and technology perspectives with insights from psychology and HR management.

2.4. *Human space and distance perception and its role in picker blocking*

Psychological research into personal space and distance perception offers valuable, complementary insights into how workers' spatial needs and perceptions influence their interactions and movements, potentially resulting in picker blocking and other phenomena in warehouse operations. IPD, which is well-documented and relevant concept in psychology, refers to the physical space individuals maintain between themselves and others (which can include objects) during close interactions and movements. This concept is influenced by many factors, including social norms, personal comfort, the specifics of a situation, and safety concerns (Mirlisenna et al., 2024). An individual's cultural background and social group membership significantly influence their sense of IPD perceptions and the willingness to uphold or increase physical distances. Wei et al. (2024) found that individuals from collectivist cultures, such as China, tend to maintain a greater distance from outgroup than ingroup members, while individuals from individualist cultures, such as Italy, exhibit more consistent distance preferences regardless of social grouping. This suggests that in culturally diverse warehouse environments, these differences may lead to varying spatial behaviours among pickers, potentially influencing congestion patterns and picker blocking.

Recent global crises have also impacted IPD preferences. Croy et al. (2024) found that during the COVID-19 pandemic, preferred distances increased globally by 54%, a shift that persisted beyond the immediate crisis. Heightened awareness of health risks led individuals to maintain greater physical distance in all types of interactions, with particularly strong effects among those with higher self-reported vulnerability to diseases. Individual differences in risk perception and anxiety also play a crucial role in how people assess their spatial surroundings. van Rijswijk et al. (2016) found that people with higher trait anxiety tend to feel unsafe in their surroundings, even when there is no actual threat. Workers who are more sensitive to their surroundings may see crowded warehouse aisles as riskier and might, as a result, subconsciously maintain a longer following distance, hesitate, or change how they move, contributing to picker blocking.

These behavioural tendencies become particularly relevant in dynamic warehouse settings. In these the presence of other workers, as well as the movement of manual and automated picking support vehicles, continuously shape spatial situations and interactions. When personal space is unexpectedly invaded, individuals often experience discomfort and adjust their behaviour, either by stepping back, pausing their movement, or modifying their workflow to accommodate perceived intrusions (Gifford, 1983). Workers may act in anticipation and avoid moving into spaces that are occupied in order to avoid the discomfort. This can further intensify congestion and lead to increased inefficiencies. Avoidance behaviours disrupt the natural flow of order picking operations and reduce the space available for manoeuvring to avoid picker blocking.

According to the EVT, when spatial expectations are disrupted, people react mentally and physically, which can impact their performance and decision-making (Berger et al., 2015). In a warehouse, unexpected proximity, for example, another picker with an AGV or manual industrial truck entering an individual's anticipated workspace, can cause momentary delays, as workers either hesitate or step aside to regain their comfort zone (Perry et al., 2015). These micro-adjustments, though seemingly minor, cumulatively increase picker blocking and reduce order-picking performance.

Individuals' perception biases also play a key role in how they judge space. Studies show that individuals often think others are closer in distance than they actually are, causing them to overcompensate in their movements (Gifford, 1983). This tendency can exacerbate picker blocking; pickers might stop too soon or make unnecessary detours to avoid what they perceive as congestion. Similarly, Edwards (1977) finds that how people regulate personal space depends on factors like their sense of control and need for stimulation. As a result, differences in stress tolerance and comfort with proximity can lead to inconsistent spacing between pickers in the same aisle.

How people perceive crowding also explains some within-aisle blocking. Crowding is not only about how many people are in a space — it is also a psychological experience shaped by expectations, the predictability of movements, and task urgency (Martínez-Sánchez et al., 2023). When order pickers expect congestion, they may adjust their behaviour in ways that either reduce or worsen picker blocking. For example, a worker perceiving high congestion may slow to allow others to move ahead, while another may attempt to rush through. These erratic movement patterns potentially increase blocking events.

Spatial behaviour in shared workspaces is also impacted by perceived safety concerns. Cho et al. (2024) find that witnessing safety violations at work heightens employee anxiety, often resulting in avoidance behaviours and reduced engagement. In high-density settings, such as warehouses, these stress reactions may appear as hesitation, greater distancing, or altered movement patterns, ultimately contributing to inefficiencies and blocking.

Picker blocking is also influenced by interpersonal differences among workers. Perry et al. (2015) find that people with higher empathy are more comfortable with close interpersonal distances than those with less empathy. These differences affect pacing and spacing, making it harder to maintain a steady picking flow. Similarly, neurodevelopmental traits and anxiety levels shape spatial preferences — individuals with social anxiety, for instance, tend to keep a greater distance from others, which can disrupt optimal picking paths (Mirlisenna et al., 2024).

These interdisciplinary insights have complemented the initial operational and technological perspectives. We next present a summary and describe our contribution to lay the ground for further analysis and interpretation below.

2.5. *Summary and contribution*

Picker blocking in manual order picking has received substantial attention in the literature, with various studies analysing its causes and strategies for mitigation. Picker blocking has been categorised into types, such as in-the-aisle and pick-column blocking, and the impact of warehouse layout, routing strategies, and storage assignment.

Winkelhaus et al. (2022) extend this research by investigating picker blocking in a hybrid environment where human pickers share a workspace with autonomous robots. The authors use the agent-based simulation model to assess different system characteristics and find that the hybrid system can enhance warehouse throughput and efficiency. Koreis (2025) further examines the role of AGVs in reducing picker blocking, specifically how the number of AGVs operating alongside human pickers in an aisle affects congestion, finding that this depends on picker density; moderate AGV integration improves performance but excessive AGV presence leads to increased blocking.

These studies, which remain at the system level, do not disentangle the micro-level mechanisms through which picker blocking affects individual task performance times. In particular, there is little evidence regarding how distinct blocking events — pick-column blocking and within-aisle blocking — contribute to delays and how much of this delay is offset by AGV assistance.

It has also been noted that the operational issues associated with picker blocking are closely linked to human concepts and perceptions regarding, for example, space, safety, congestion, and interactions, that are addressed in psychology and HR management research. What remains largely unexplored is how these human factors interact with operational blocking events to shape picker behaviour and performance. Combining operational data with psychological perspectives can help uncover mechanisms such as hesitation, anticipatory waiting, or detours that amplify blocking effects. A theoretically grounded, data-driven approach would explain not only how often blocking occurs, but why it leads to performance losses under varying technological setups.

In the following, we address this research gap by empirically examining, for the first time in a real mixed-technology warehouse environment, how pick-column and within-aisle blocking affect the average task performance time of individual pickers and whether AGV assistance mitigates the blocking effect. We use a large operational dataset (N = 490,398 picks by 205 pickers) and apply linear mixed-effects models to capture within- and between-picker variation. By linking operational data and human factor theory, this study provides actionable insights for warehouse design, routing strategy, and AGV integration.

3. Methodology

3.1. Empirical order picking setting

We worked closely with a German retailer that has multiple warehouses, handling both perishable and non-perishable products. The warehouse studied here houses 4957 distinct non-perishable products, distributed across 49 aisles and organised into 10 picking zones. The study warehouse, where the pilot test was conducted, features an aisle with 120 pick locations, evenly distributed, with 60 pick locations per shelf. The aisle is 3.85 m wide and is systematically organised to group similar products together, based on factors such as demand frequency, product type, and handling requirements. This ensures that frequently picked products are placed in more accessible locations than less frequently picked products. The travel distance between each pick location is 0.8 metres, with the products stored on euro pallets that define the width of each pick location. In the warehouse under investigation, non-cooled sections are operated as picker-to-parts order-picking systems with vehicle support by industrial trucks and AGVs. The order pickers start on the right side of the aisle and move along it following a U-shaped layout, a design commonly used in warehousing where the receiving and shipping areas are located at the same end of the building (Henn et al., 2013).

In the analysed picker-to-parts order picking setting, each batch performed by one picker typically spans two aisles and consists of an average of 76 batch positions. A batch position corresponds to one or more picks at a given pick location, with a mean of about two picks per position. Each pick typically involves a packaging unit containing roughly five products, resulting in approximately 10 products being handled per batch position. On average, there are around 40 batch positions per batch in the focal aisle. This concentration of pick activity allows the systematic observation of pick-column and within-aisle blocking events and their cumulative effect on task performance time.

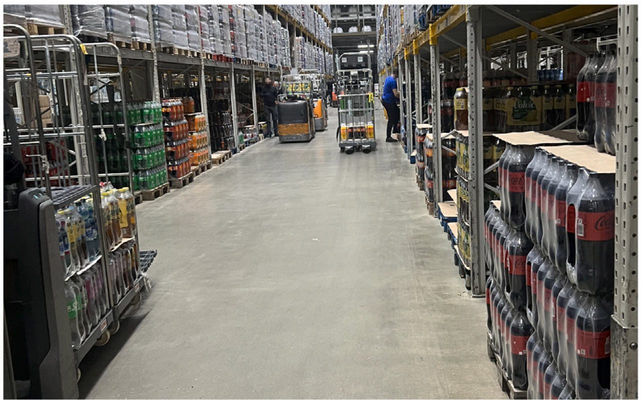

Fig. 1. Order picking process under investigation.

The main focus of the pilot study we observed was the introduction of an order picking approach, where order pickers worked alongside autonomous and manually operated industrial trucks, all navigating within the same aisles. The pilot test we accompanied involved four AGVs, the first of which has been operational since 1 June 2022, with additional units gradually integrated into the system in January 2023. These AGVs were deployed in dedicated aisles. All other order pickers continued to work with manually operated industrial trucks and were not engaged in a human–AGV collaborative order picking system. Fig. 1 illustrates the order picking process under investigation.

3.1.1. Prior technology and new technology generation

Our literature review revealed the lack of research on similar systems. In the analysed workspace, human operators with AGVs and human operators with manually operated industrial trucks navigated the warehouse aisles to retrieve products from the shelves, with each group having distinct characteristics.

Prior technological generation: The order picker was equipped with a motorised order picking vehicle, commonly known as an industrial truck. This manually operated vehicle, capable of reaching speeds of up to 12 km/h, required the picker to actively control its navigation through the warehouse aisles. The picker was also responsible for accurately positioning the vehicle at each designated pick location to ensure efficient product retrieval. Pickers using the prior technology were already familiar with the operation of industrial trucks, allowing them to navigate efficiently without further extensive training. Their practical knowledge included manoeuvring in narrow aisles, optimising vehicle positioning, and handling order picking tasks while operating the truck.

New technology generation: The AGV is designed to assist order picker by automatically following the order picker along the aisles during order picking. The AGV detects the order picker's position and adjusts its speed and movement accordingly, with speeds of up to 12 km/h. This is made possible by sensors and a remote positioning system that tracks the order picker within a range of up to 15 m. The AGV moves alongside the picker, maintaining an ideal distance for products to be picked and placed on it. A key feature of the AGV is its ability to navigate the aisle independently. It uses a laser scanner to continuously monitor its surroundings and detect obstacles such as shelves, walls, or other equipment. The AGV maintains a minimum distance of 50 cm from the shelves to ensure safety while making efficient use of space.

If an object blocks its path and cannot be avoided, the AGV stops until the area is clear, reducing the risk of accidents. The AGV operates in assistance mode, meaning it follows the order picker without requiring manual control. The picker can focus entirely on picking tasks while the AGV positions itself. Depending on the pick location, the AGV can align to the right, left, or centre of the aisle, with alignment adjusted via a remote control. However, changing aisles is only possible manually, requiring the picker to take control of the vehicle. The order picker has the flexibility to decide whether to walk to the next pick location with the AGV following or to drive the vehicle there.

Although pickers operating with the new-generation technology were already familiar with the warehouse layout, product locations, and standard order picking processes, they required specific training on the handling and integration of AGVs into their workflow. Pickers working with the new-generation technology participated in a structured training program. The program familiarised workers with AGV functionalities, safety protocols, and operational procedures. Included in the training were the proper handling of AGVs, the role of laser scanners and sensors in obstacle detection, and the ability to switch between active (walking and AGV following) and manual (riding) mode. The order pickers also learned to use the remote control efficiently to optimise AGV positioning during order picking.

Using previous technology, a high pick density requires the order picker to frequently mount and dismount the vehicle. When the order picker receives picking instructions through assistive technology, they either drive or walk to the designated location in the aisle where products are to be retrieved. Once in the aisle, the picker with an AGV steps off the vehicle, which then autonomously follows as they move along the aisle. Compared to manually operated industrial trucks, this system eliminates the need to get on and off the vehicle for each pick (Tutam and de Koster, 2024).

3.1.2. Picker blocking in the scenario under investigation

We identify two main types of picker blocking in the warehouse studied: pick-column blocking and within-aisle blocking. Fig. 2 illustrates picker blocking in the scenario under investigation.

Pick-column blocking (a and b in Fig. 2) occurs when the order picker with their vehicle is positioned at pick location n, blocking access to pick locations $n-1$, n, and $n+1$. This obstruction is a direct result of the vehicle's length, which extends beyond a single pick location, effectively covering multiple adjacent positions. Given that the standard industrial truck or AGV used in warehouse order picking is designed to accommodate multiple products on one or two transport aids, its physical footprint spans approximately the width of three neighbouring pick locations. With the new-generation technology, the AGV's safety systems and collision avoidance mechanisms cause it to (a) automatically stop behind the blockage, preventing any further approach. Once the blockage is cleared (b), the AGV can autonomously advance to the previously blocked pick location. This ensures a seamless picking process without the need for manual repositioning. Alternatively, the order picker may choose to wait behind the blockage (a) until the pick location becomes available, at which point both the picker and the AGV can proceed without interruption. In the prior technological generation (b), the picker either walks an additional route to retrieve the product from the blocked pick location, returning to the vehicle to place the product, or waits until the picker ahead completes the pick event and clears the path.

Within-aisle blocking occurs when multiple order pickers operate within the same aisle, with movement restricted by the limited aisle width. In this scenario (c and d above), a picker is obstructed while attempting to move to the next pick location, potentially unable to proceed due to another picker occupying the space ahead. Depending on the aisle density and the availability of manoeuvring space (c), the order picker may either wait for the obstruction to clear or, if possible, bypass the blockage. In high-density settings where overtaking is not feasible, the picker must remain stationary until the blocking picker moves forward, while in lower-density situations (d), the picker may have the opportunity to navigate around the obstruction and continue the picking process. If sufficient space is available (d), the AGV can autonomously navigate around the blockage while ensuring compliance with safety protocols, allowing for continuous operation without manual intervention. Simultaneously, if the distance between two successive pick locations is short (c), the picker may proceed by foot to the next pick location to retrieve the required products, and the AGV will automatically follow. Alternatively, (d) the picker has the option to deactivate the assistance mode and manually control the AGV, riding it past the blockage when necessary. With the prior technological generation, the order picker has only two options: (c) either wait until the obstruction clears or (d) actively manoeuvrer around the blockage by repositioning the industrial truck. Whereas with the new-generation technology, the AGV can autonomously adapt its movement based on available space and safety constraints, order pickers working with the previous technology must take full control of their vehicles.

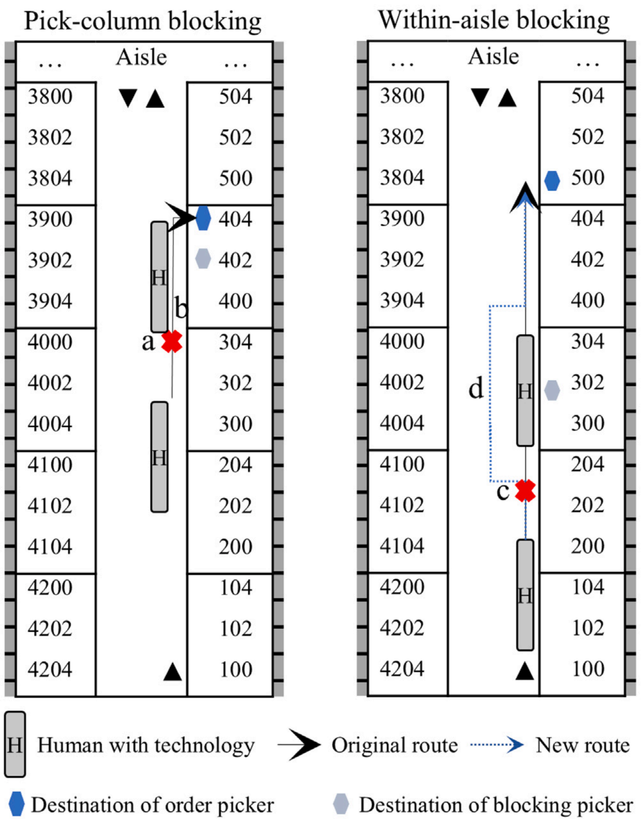

Fig. 2. Picker blocking in the scenario under investigation.

3.2. Historical data

The historical data under investigation were collected between 1 February 2023 and 30 September 2023. The dataset extracted from the company's warehouse management system (WMS) included data on batch identification (ID), batch position, picker ID, aisle, pick location, number of products per batch position, the volume and weight of the product, and the timestamps of each pick. Since the use of AGVs was largely concentrated in aisles 7-10, we focused our analysis on aisle 7, where the highest activity levels were recorded.

The reliability of the results was improved by implementing a data cleaning process following the best practices outlined by Batt and Gallino (2019). During regular shifts, order pickers took scheduled and unscheduled breaks, which led to interruptions in the picking process.

Table 1
Descriptive statistics.

No.	Variable	Operationalisation	VIF	Mean	SD
DV	Task performance time	Continuous	–	17.66	11.72
IV_1	Pick-column blocking	Binary dummy	1.33	0.37	0.49
IV_2	Within-aisle blocking	Binary dummy	1.28	0.66	0.47
CV_1	Product weight	Continuous	1.95	9.48	4.88
CV_2	Product volume	Continuous	1.22	16.38	4.87
CV_3	Travel distance	Continuous	1.04	4.79	5.58
CV_4	Batch position	Continuous	1.15	75.97	27.23
CV_5	Products per batch position	Continuous	2.05	10.01	6.42
CV_6	Total pickers in the aisle	Continuous	1.02	5.11	4.64
CV_7	AGV assistance	Binary dummy	1.00	0 = Prior technology generation (80.62%) 1 = New technology generation (19.38%)	

However, these breaks were not always recorded correctly; pickers occasionally forgot to log their start or end times. Additionally, pickers occasionally performed other warehouse-related tasks, such as tidying their workspace or handling non-picking activities, without formally registering these. As a result, some picking times appeared unusually long, not accurately reflecting actual performance.

We addressed these inconsistencies by establishing thresholds to filter out unrealistic pick events. Any pick event taking less than 2 s or more than 90 s was excluded from the analysis. This threshold was based on operational insights and technical constraints. Picking and confirming a product in under 2 s was deemed physically impossible, while durations exceeding 90 s were often indicative of interruptions such as breaks or technical issues rather than standard picking actions. The warehouse manager was consulted to ensure these thresholds aligned with operational conditions. Further refinements were applied to maintain data accuracy. Only weights between 0.01 kg and 29 kg per pick event were considered, ensuring unrealistic entries were excluded. Pick-IDs containing more than 30 products were also removed, as such cases typically involved the retrieval of entire pallets rather than individual products, which did not align with standard picking operations. To ensure only realistic vehicle movement was included, picks were excluded if the recorded average travel speed exceeded 3.33 m/s since this speed was not technically feasible. Given that the trucks had a maximum speed of 12 km/h, this threshold ensured that only valid picking tasks were analysed. After validating all data cleaning steps with the company, the final dataset included $N = 490{,}398$ pick events performed by 205 order pickers. Of these, 19.38% involved new-generation technology, while 80.62% were completed using the prior generation's technology.

In addition to the data cleaning procedure, we performed an exploratory analysis of the distributions of all variables included in the econometric model. Task performance time showed a right-skewed distribution, as expected in warehouse settings where most pick events are completed quickly but a small proportion of tasks take substantially longer. Product weight and product volume exhibited relatively compact inter-quartile ranges, confirming that most products fall within a narrow weight and volume band, while a small number of heavier or bulkier products extend the upper tails. The travel distance between pick locations was concentrated in short movements (median of approximately 4 to 5 m), with a small fraction of longer movements representing aisle changes or far-apart picks. Most pick events involved between 7 and 12 products each, with a few larger pick events that likely corresponded to full-case or multi-unit replenishment. The number of pickers simultaneously present in the aisle ranged between 4 and 6 for most observations, with higher densities occurring rarely. Only in exceptional peak periods did the number of concurrent pickers exceed 10. Finally, the batch position indices confirmed that batches were predominantly in the range of 50 to 100 positions, with larger batches in the minority but operationally plausible. Overall, the distributions confirm that the dataset captures realistic warehouse operations, and the few extreme values present are consistent with operational edge cases rather than data errors. The corresponding means and standard deviations for these variables are summarised in Table 1.

4. Data and method

4.1. Variables and econometric framework

4.1.1. Dependent variable

Our dependent variable is task performance time, defined as the time elapsed in seconds between the completion of two successive pick events $i-1$ and i at the batch-position level, including the picking of products from pick location i. The task performance time comprises the time a picker takes to set up, travel to a pick location, search for the product, retrieve the required number and record the pick completion in the WMS via the digital assistive device. Average task performance time is operationalised as a continuous metric variable. Note that a positive coefficient for task performance time is related to the higher predicted time for completion of the order-picking task, implying a negative impact on order-picking task performance.

Following common practice in the organisational learning literature, we took the natural logarithm of task performance time (Argote et al., 2021). Task performance times are often highly skewed, meaning that a small number of very extended tasks can disproportionately affect the average performance time. Logarithmic transformation helps reduce skewness and approximate a symmetric distribution of residuals, which is a key assumption for many statistical models. In our dataset, as noted above, the task performance times were indeed strongly right-skewed, with a small proportion of very long pick events. Applying the natural log transformation substantially reduced skewness and improved residual symmetry, thereby ensuring more robust parameter estimation and facilitating the interpretation of regression coefficients in percentage terms.

4.1.2. Independent variables

The independent variable IV_1, pick-column blocking, captures whether an order picker j is hindered by one or more order pickers working at the same or nearby pick locations during a specific pick-location visit i. This blocking occurs when another picker is active at the same pick location (n) or an adjacent location, ($n-1$, $n+1$), while the timestamps of each pick event overlap.

Importantly, pick-column blocking also occurs when another picker is positioned at pick location $n+1$. Due to the length of the vehicle, which extends beyond a single pick location, access to pick location n is obstructed even if the adjacent picker is not at the exact same location but one position ahead. Since industrial trucks are designed to accommodate multiple products on transport aids, their physical footprint covers multiple neighbouring pick locations. Consequently, when a picker at n attempts to retrieve products, the presence of another picker at $n+1$ prevents direct access to the pick location n, resulting in a blocking effect.

We systematically determine pick-column blocking by assessing each pick event based on several factors. First, the picker's specific pick location at a given pick event i is identified. Next, the presence of at least one other order picker j working at the same or an adjacent pick location ($n-1$, $n+1$) is considered. Any overlap in the picking process is also examined, meaning that the timestamps of the start and end of the order picking tasks intersect. Lastly, the relative position of the pickers is evaluated, with only those positioned behind another picker affected by pick-column blocking; the picker in front experiences no obstruction.

Pick-column blocking is defined as follows:

$$\mathrm{IV}_{1i} = \begin{cases} 1, & \text{if picker } j \text{ is obstructed by another picker at} \\ & (n-1, n, n+1) \text{ with time overlap} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

We operationalise IV_1 in the dataset by combining the date and time stamps into continuous intervals and parsing storage addresses into aisle and column identifiers, with the column index n representing the physical pick location. For each pick event, we identified all other pickers active in the same aisle whose picking intervals overlapped in time. An overlap means that the time period in which another picker was active intersected with the time period of the focal picker's event — in other words, the other picker started before the focal picker finished, and finished after the focal picker started ($t_i^{\text{start}} \leq t_k^{\text{end}}$ and $t_i^{\text{end}} \geq t_k^{\text{start}}$). This captures three cases: (1) the other picker started and ended during the performance of the focal picker's task, (2) the other picker's task started earlier and ended during the focal task, or (3) the other picker's task fully spanned the period taken to complete the focal task. Among these overlapping events, we then selected those located at $n-1$, n, or $n+1$. IV_1 was set to 1 if at least one such overlapping picker was positioned ahead of the focal picker (blocking access), and 0 otherwise. This procedure ensures that only the picker who is obstructed receives a value of one, while the picker in front is coded as unblocked.

We assessed robustness by repeating the analysis with stricter definitions of time overlap, requiring that two pick events overlap by at least three seconds and, in a second step, by at least five seconds. This approach ensures that very brief encounters are not counted as blocking events. In all cases, the direction and significance of the results were unchanged, confirming that our findings are not sensitive to the exact definition of the overlap.

The independent variable IV_2 within-aisle blocking, indicates whether an order picker j is hindered by another picker operating on the same side of the aisle during a specific pick-location visit i. This situation arises when another picker is positioned further down the aisle on the same side, blocking the path to the pick location. As a result, the affected picker must either wait behind the obstructing picker until the pick event is completed or attempt to pass, which requires additional time. To ensure analytical consistency, within-aisle blocking is only considered when both the affected and the obstructing picker are operating on the same side of the aisle, whether left or right. Only in this case does within-aisle blocking occur.

Each pick event is assessed based on several factors to systematically determine whether within-aisle blocking has occurred. First, the picker's specific pick location at a given pick event i is identified. Next, it is determined whether at least one other order picker j is operating within the same predefined aisle zone (left or right side). Additionally, any overlap of the timestamps of each pick event is examined, meaning that the start and end of the order picking tasks intersect. Finally, the relative position of the pickers is evaluated, considering whether the affected picker is positioned behind another picker who obstructs movement within the aisle. In such cases, the picker in the back may experience delays or restricted movement, whereas the picker in front remains unaffected.

Within-aisle blocking is defined as follows:

$$\mathrm{IV}_{2i} = \begin{cases} 1, & \text{if picker } j \text{ is obstructed by another picker on the same} \\ & \text{side of the aisle with a time overlap} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

We operationalised IV_2 by first partitioning each aisle into two zones, representing the left and right side based on column indices. For each pick event, we identify all other pickers active in the same zone with overlapping time intervals, where overlap is defined as the intersection of the two picking periods ($t_i^{\text{start}} \leq t_k^{\text{end}}$ and $t_i^{\text{end}} \geq t_k^{\text{start}}$); that is, both pickers were simultaneously present on the same side of the aisle. Among these overlapping events, we retained those where the other picker's column index n_k was greater than the focal picker's pick location n, indicating that the obstructing picker was located further down the aisle and blocking the path forward. In this situation, the focal picker must either wait until the other picker completes the task or attempt to pass the picker and the vehicle, which typically takes additional time. IV_2 was set to 1 if at least one such overlapping picker was detected, and 0 otherwise. As with IV_1, this operationalisation ensures that only the picker who is physically hindered receives a value of one, with the picker in front remaining unblocked.

We verify the robustness of IV_2 by performing the analysis again using stricter definitions of time overlap. Specifically, we required that the simultaneous presence of the focal picker and the obstructing picker on the same side of the aisle lasted at least three seconds and, in a second step, at least five seconds. This additional threshold helps ensure that only sustained blocking situations, rather than very brief encounters, are counted as within-aisle blocking events. The results remained qualitatively identical, indicating that our findings are not sensitive to the exact specification of the overlap criterion.

4.1.3. Control variables

For the selection of control variables, we apply the decision-making framework proposed by Bernerth and Aguinis (2016). On this approach, each control variable must be theoretically justified, empirically supported, contextually relevant, and transparently reported to ensure that its inclusion meaningfully contributes to explaining variation in the dependent variable. We include several control variables for product, batch, and storage characteristics, as set out below.

- Product weight (CV_1): This quantifies the weight (in kilograms) of the product handled in each pick event, which directly influences the physical effort required in human-centred order-picking systems (Battini et al., 2016). As product weight increases, so too does the energy needed for pickers to lift, carry, and transport these products. The significant increase in physical effort can lead to quicker onset of fatigue, reduced picking efficiency, and a longer task performance time (Elbert and Muller, 2017). Given the substantial variation in weight across products in our warehouse, controlling for this factor helps ensure that observed differences in the time taken to perform a task reflect the technological effect of AGV assistance rather than variation in the physical workload.
- Product volume (CV_2): The physical dimensions (in litres) of the product handled in a pick event are quantified to capture the space required for handling and stacking during manual order picking operations. We integrate the volume per product unit in litres as a continuous variable to control for the article dimensions impacting task performance time. Higher product volume can complicate the stacking and organising process, as bulkier products may require additional handling and space management, potentially extending the task performance time (Ranasinghe et al., 2024). Controlling for product volume is therefore necessary to isolate the technological effect of AGV assistance from performance differences stemming from variation in item size and the associated handling requirements in the warehouse environment.
- Travel distance (CV_3): This refers to the distance (in metres) between two successive pick locations, specifically between pick events $i-1$ and i, at the batch-position level. Longer travel distances inherently require greater movement effort, which impacts the task performance time by extending the time per pick (Battini et al., 2015). Since travel distance varies substantially across batches and aisles, controlling for this factor ensures that observed performance effects can be attributed to AGV assistance rather than route-specific conditions.

- Batch position (CV_4): This represents all the pick events (N = 490,398 batch positions in total) during one batch processed by an order picker. Note that each pick event may include picking more than one product. A product that has been retrieved needs to be organised and placed into an existing order, which comprises the preceding pick positions (Bayram et al., 2022). As the batch progresses, the available space on the load unit decreases, making the placement of additional products more complex. This rising spatial complexity, combined with cumulative physical and cognitive workload, can lead to longer task performance times towards the end of a batch. Therefore, controlling for batch position helps to separate effects arising from intra-batch task progression and load organisation from those attributable to AGV assistance.
- Products per batch position (CV_5): This defines the quantity of products retrieved from the pick location in each pick-location visit (Loske et al., 2025). Handling a larger quantity of products per batch position may result in longer task performance times (Bayram et al., 2022). This intensifies the physical and cognitive workload during the picking process, which can have a negative impact on task performance time. In the warehouse under investigation, the number of products per batch position varies substantially across pick locations and order types. For example, pickers working in the beverages section often handle heavier multi-unit cases, while those in the confectionery section typically process a larger number of lightweight single items. Controlling for this variation helps ensure that observed differences in task performance reflect the technological impact of AGV assistance rather than discrepancies in manual handling effort or product-specific complexity.
- Total pickers in the aisle (CV_6): Total pickers in the aisle refers to the number of pickers present in a specific aisle during the order picking process. We aggregate the data to ensure that the recorded values represent the number of order pickers working simultaneously within the aisle. The total count was rounded to the minute. This variable captures workforce density within the aisle, which can influence task performance time, movement patterns, and the potential for delay (Koreis et al., 2025b). Picker density varies considerably across areas and time. For example, peak congestion often occurs in high-turnover sections, for example, beverages, where congestion is particularly high during the summer months when demand for drinks rises sharply; others may experience lower overlap. Controlling for this factor ensures that estimated performance differences are not driven by temporary crowding effects but reflect the technological contribution of AGV assistance to smoother coordination of movement.
- AGV assistance (CV_7): AGVs are designed to reduce manual transport efforts by assisting human pickers in moving products efficiently during order picking operations (Löffler et al., 2021). In typical picker-to-parts order-picking systems, AGVs follow human workers and transport the picked products, allowing pickers to focus on retrieval tasks rather than vehicle handling (Pasparakis et al., 2021). Given that we observe prior and new generations of technology sharing a workspace, the control variable *AGV assistance* is a dichotomous operationalisation of whether prior or new technology is applied. $AGV\_assistance_{ij}$ for pick-location visit i and picker j is equal to 1 when pick location i is visited with AGV assistance and 0 otherwise:

$$\mathrm{CV}_{7_{ij}} = \begin{cases} 1, & \text{if pick location is visited by an order picker with} \\ & \text{the assistance of new technology} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Table 2
Correlation table.

	DV	IV_1	IV_2	CV_1	CV_2	CV_3	CV_4	CV_5	CV_6	CV_7
DV	1.00									
IV_1	0.08	1.00								
IV_2	0.05	0.25	1.00							
CV_1	0.24	0.03	0.02	1.00						
CV_2	0.11	0.06	0.11	0.07	1.00					
CV_3	−0.03	−0.02	0.01	−0.05	−0.12	1.00				
CV_4	0.03	−0.05	−0.11	0.02	−0.32	−0.09	1.00			
CV_5	0.32	0.06	0.05	0.69	0.24	−0.08	−0.06	1.00		
CV_6	0.01	0.07	0.10	0.00	−0.01	0.01	0.00	0.00	1.00	
CV_7	−0.10	0.07	0.08	0.00	0.05	−0.02	−0.03	0.01	0.00	1.00

4.2. Econometric statistics

We calculate the descriptive statistics and the variance inflation factor (VIF) for a more complete understanding of the variables used in the model. Table 1 presents the descriptive statistics for focal variables.

There are no notable concerns regarding multicollinearity among the predictor variables; all VIF values remain below the commonly accepted threshold of 5.00. Since VIF measures collinearity among independent and control variables, it is not applicable to the dependent variable. VIF quantifies the extent to which the variance of a regression coefficient is inflated due to correlation among predictor variables. Higher VIF values indicate stronger collinearity. The VIF for each predictor was determined using the following formula:

$$VIF(X_j) = \frac{1}{1 - R_j^2} \tag{4}$$

We also perform a cross-correlation analysis to check for possible correlation effects among the dependent, independent and control variables. The results are summarised in Table 2, which indicates that the inclusion of all variables in the analysis was valid.

4.3. Mixed-effects model

This study employs a mixed-effects regression model with a random intercept for each order picker using R Studio (Version 2024.12.0) and the *nlme* package. Specifically, the *lme* function was utilised to fit a linear mixed-effects model, following the approach outlined by Brown (2021). The *flexplot* and *lme4* packages were also applied to support the data analysis.

The literature on order picking employs various approaches to assess the impact of different factors on performance, which is typically measured as task performance time. Lucchese et al. (2024) explore how cognitive assistive technologies influence task performance time in a controlled laboratory environment by analysing correlations between a single predictor variable and task completion time. This type of bivariable comparison is not suitable for the present study, as various other factors must be accounted for in real-world conditions, including product weight, product volume, and travel distance. The controlled nature of the experimental setting, for example, in Lucchese et al. (2024), limits its applicability to large-scale warehouse operations, where additional variables influence task performance.

Batt and Gallino (2019) examine the performance effects of searching for products in a manual, real-world order picking setting and applied an accelerated failure time model (AFTM) (Crowther et al., 2023). This survival analysis technique assumes that covariates either speed up or slow down the time to an event by a constant factor. It does not incorporate random effects for variability at the group level nor allow for cross-level interactions. Loske et al. (2024b) extend this approach by employing a mixed-effects log–logistic AFTM to analyse the processing time in a cold retail supply chain. Unlike standard AFTM models, which assume a single regression line for all order pickers, the applied mixed-effects specification allows for individual-specific random effects by fitting separate regression lines per picker ID. This hybrid approach significantly improves model fit and accounts for human factors, such as differences in picker experience and efficiency.

In a standard mixed-effects model, variability in task performance is estimated without making assumptions about time-to-event distributions. By contrast, a mixed-effects AFTM specifically models the time until task completion, incorporating principles of survival analysis and accounting for individual differences through random effects. Since both allow for analysis of task performance time based on start and end times, the choice of approach depends on whether time-to-event modelling (AFTM) or direct estimation of task performance time (mixed-effects regression) is preferred. Mixed-effects models are recommended when both within- and between-picker differences are theoretically expected or empirically observed, such as through intra-class correlation coefficient (ICC) measurements (Bliese et al., 2018). Research by Koreis (2025), Loske et al. (2024a) and Loske et al. (2025) demonstrates that mixed-effects models effectively capture both fixed and random effects, enabling variability to be modelled within and across groups. In summary, previous studies on order picking have employed bi-variable analyses, AFTM, mixed-effects AFTM, and mixed-effects models. The present study utilises a mixed-effects model due to the significant within- and between-picker differences, as confirmed through ICC evaluation.

4.4. Econometric specifications

Given the presence of within-picker and between-context variation, the mixed-effects model includes a random intercept α_{0jt}, allowing order picker j to vary in their baseline task performance time across weekday-specific time blocks t. This specification reflects the idea that individual performance may systematically differ not only across pickers, but also depending on when during the week and workday the picking activity occurs. By modelling the interaction of picker and temporal context, the model captures both individual-level heterogeneity and temporal dynamics in performance.

Thus, the random main intercept α_{0jt} is specified as follows:

$$\alpha_{0jt} = \gamma_{00} + \upsilon_{0jt} \tag{5}$$

where γ_{00} represents the overall grand intercept across all picker–time-block combinations, and υ_{0jt} captures the deviation of picker j in time block t from this overall mean. The model thus reflects both structural and situational influences on task performance, ensuring a more accurate and nuanced estimation of effects.

Model (1) includes fixed effects to examine the influence of control variables on task performance time. Specifically, the model controls for pick-event product weight (β_1) and volume (β_2), travel distance between two successive pick locations (β_3), the sequential batch position (β_4), the number of products per batch position (β_5), the total number of pickers in the aisle (β_6), and the operational setting, distinguishing between prior- and new-generation technologies (β_7). All variables are indexed at the observation level ijt, referring to individual pick events i by order picker j in weekday-specific time block t. These factors account for product-specific, environmental, and workload-related effects on task performance time.

In Model (2), we incorporate the independent variables pick-column blocking (β_8) and within-aisle blocking (β_9) to assess their effect on task performance time. Both variables are defined at the observation level, ijt. Pick-column blocking occurs when an order picker is hindered by another picker operating at the same or an adjacent pick location, potentially delaying task execution. Similarly, within-aisle blocking occurs when an order picker must wait behind or manoeuvre around another picker operating on the same side of the aisle, thereby increasing task performance time.

Model (3) introduces the interaction term $\beta_{10}\,(AGV\_assistance_{ijt} \times pick - column\ blocking_{ijt})$ and $\beta_{11}\,(AGV\_assistance_{ijt} \times within - aisle\ blocking_{ijt})$ to examine whether the effect of picker blocking on task performance time differs between prior- and new-generation technologies. These interaction terms allow us to investigate whether AGV assistance mitigates or amplifies the impact of pick-column blocking and within-aisle blocking. A significant negative coefficient for the interaction terms would indicate that there is a smaller increase in task performance time due to blocking in AGV-assisted compared to manual order picking, suggesting a performance advantage in shared-workspace environments. Conversely, a positive coefficient would imply that AGV-assisted order picking is more susceptible to congestion-related disruptions.

Finally, the model incorporates τ_{ijt} as a control variable to account for time-related influences, including month, day of the week, and hour of the day. These temporal adjustments help us isolate variations in task performance time that may arise due to operational schedules or fluctuations in workload distribution. Lastly, ϵ_{ijt} represents the error term. The final model, Model (3), is formulated as follows:

$$\begin{aligned}\log\left(DV_{ijt}\right) = {} & \alpha_{0jt} + \beta_7 AGV\_Assistance_{ijt} + \beta_8 Pick - Column\ Blocking_{ijt} \\ & + \beta_9 Within - Aisle\ Blocking_{ijt} \\ & + \beta_{10}(AGV\_Assistance_{ijt} \times Within - Aisle\ Blocking_{ijt}) \\ & + \beta_{11}(AGV\_Assistance_{ijt} \times Pick - Column\ Blocking_{ijt}) \\ & + \sum_{n=6}^{N} \beta_n\, Control_{ij} + \tau_{ijt} + \epsilon_{ijt}\end{aligned} \tag{6}$$

$$\alpha_{0jt} = \gamma_{00} + \upsilon_{0jt} \tag{7}$$

We assess the appropriateness of a mixed-effects model by first calculating the ICC for task performance time. The ICC quantifies the proportion of total variance in the dependent variable that is attributable to differences between groups, in this case, individual order pickers j within specific temporal contexts. Specifically, we group observations based on unique combinations of order picker j and temporal segments of the workday, defined by the day of the week and three distinct time blocks: early morning, mid-morning, and midday/early afternoon. These blocks are selected to reflect operationally relevant intra-day variations, such as congestion patterns, break schedules, supervision intensity, and physical fatigue. For instance, picker performance at the beginning of a shift may differ from performance just before lunch or later in the shift. By modelling the performance of pickers within these structured periods, the analysis accounts for both individual and temporal heterogeneity. The resulting ICC of 0.101 indicates that 10.1% of the variance in task performance time is attributable to between-group variation. This justifies the use of a hierarchical mixed-effects model that incorporates both individual picker characteristics and shift-based temporal dynamics.

The inclusion of a random intercept in our mixed-effects model is theoretically and empirically justified. Each pick event represents one observation in the dataset, but these observations are not statistically independent: pick events are repeatedly performed by the same order pickers within shared temporal and spatial contexts. This hierarchical data structure leads to within-group resemblance (Stock, 2020), as performance in one pick event is likely to be more similar to that of the same picker (or during the same time block) than to that of a different picker. From a theoretical standpoint, individual order pickers exhibit persistent differences in their baseline time for task performance due to experience (Koreis, 2025), and work habits (Rilke et al., 2025). Contextual influences such as shift timing (Xu and Hall, 2021), fatigue (Battini et al., 2017), or aisle congestion (Koreis et al., 2025b) further affect average performance levels within specific time blocks.

These latent sources of heterogeneity cannot be fully captured by observable control variables. Allowing each picker–time combination to have its own intercept captures systematic mean shifts in

Table 3
Regression results for main model.

	Dependent variable: Log(Task performance time)		
	Model (1)	Model (2)	Model (3)
Main effects			
Pick-column blocking		0.090 (0.002)	0.098 (0.002)
		$p < 0.01$	$p < 0.01$
Within-aisle blocking		0.058 (0.002)	0.061 (0.002)
		$p < 0.01$	$p < 0.01$
Interaction terms			
AGV assistance × Pick-column blocking			−0.035 (0.005)
			$p < 0.01$
AGV assistance × Within-aisle blocking			−0.021 (0.005)
			$p < 0.01$
Control variables			
Product weight	0.002 (0.0001)	0.002 (0.0001)	0.002 (0.0001)
	$p < 0.01$	$p < 0.01$	$p < 0.01$
Product volume	0.001 (0.00004)	0.001 (0.00004)	0.001 (0.00004)
	$p < 0.01$	$p < 0.01$	$p < 0.01$
Travel distance	0.001 (0.0002)	0.001 (0.0002)	0.001 (0.0002)
	$p < 0.01$	$p < 0.01$	$p < 0.01$
Batch position	0.004 (0.0001)	0.004 (0.0001)	0.004 (0.0001)
	$p < 0.01$	$p < 0.01$	$p < 0.01$
Products per batch position	0.030 (0.0002)	0.030 (0.0002)	0.030 (0.0002)
	$p < 0.01$	$p < 0.01$	$p < 0.01$
Total pickers in the aisle	0.005 (0.0005)	−0.002 (0.001)	−0.002 (0.001)
	$p < 0.01$	$p < 0.01$	$p < 0.01$
AGV assistance	−0.369 (0.024)	−0.380 (0.024)	−0.356 (0.025)
	$p < 0.01$	$p < 0.01$	$p < 0.01$
Pickers	205	205	205
Observations	490,398	490,398	490,398
R_c^2	0.233	0.240	0.242
AIC	$883,296.800$	$879,589.100$	$879,518.300$
BIC	$883,407.700$	$879,722.100$	$879,673.500$
Log likelihood	$-441,638.400$	$-439,782.500$	$-439,745.100$

Note: Clustered robust standard errors in parentheses. P-values below coefficients; small values as $p < 0.01$.

task performance time that arise from these unobserved factors and corrects for the violation of the independence assumption inherent to standard regression models. Empirically, the ICC of 0.101 confirms that a considerable portion of variance in task performance time stems from between-picker rather than within-picker variation. We evaluate the model specification by comparing variants with random slopes for blocking variables using likelihood-ratio tests and information criteria. These extended specifications do not significantly improve model fit ($p > 0.05$). Accordingly, we retain a random intercept-only structure as the most appropriate and theoretically consistent model specification.

We further evaluate model fit and report both the marginal R_m^2 and conditional R_c^2 values, following the approach in Nakagawa et al. (2017). The marginal R_m^2 represents the proportion of variance explained solely by the fixed effects in the model, whereas the conditional R_c^2 accounts for both fixed and random effects, capturing the total explanatory power of the model, including picker-specific deviations.

For our final model, Model (3), we obtain the following results:

$$R_m^2 = 0.149, \quad R_c^2 = 0.242 \tag{8}$$

These values indicate that, while a considerable portion of the variance in task performance time is explained by the fixed predictors, the model's explanatory power is enhanced by the inclusion of random effects, such as differences between individual pickers. This finding aligns with prior research, which suggests that incorporating individual-specific variability is crucial in order-picking environments with heterogeneous worker performance (Koreis, 2025; Loske et al., 2022, 2024b).

5. Empirical results

5.1. Impact of picker blocking on task performance time

The regression results are formatted and presented using the stargazer package in R Studio Version 2024.12.0 (Hlavac, 2022) to display the models in a structured and concise manner, thereby facilitating the interpretation of key coefficients and significance levels.

In addition to R_c^2, we utilise the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to evaluate model fit. The AIC measures the balance between model complexity and model fit, with lower values indicating a better model. The BIC similarly penalises overly complex models, favouring those that achieve a good fit with fewer parameters. As presented in Table 3, Model (3) exhibits the lowest AIC and BIC, signifying that it is the model that best fits the data. Consequently, Model (3) is selected for further interpretation. The empirical results are summarised in Table 3.

Pick-column blocking (IV_1): In Model (2), we incorporate the key independent variables related to congestion: pick-column blocking and within-aisle blocking. This allows us to directly examine their main effects on task performance time without having accounted for interaction effects with AGV assistance. This provides a baseline understanding of how each type of picker blocking affects performance across the full sample, prior to considering the moderating effects of AGV assistance.

The coefficient for pick-column blocking ($\beta_8 = 0.090, p < 0.01$) indicates this variable has a significant positive effect on task performance time. Transforming the coefficient using ($e^{0.090} - 1$), this corresponds to an approximate 9.4% increase in task performance time. This suggests that when an order picker experiences pick-column blocking, the time required to complete a pick event increases, likely due to additional waiting time and reduced efficiency caused by other pickers working at the same or an adjacent pick location.

Within-aisle blocking (IV_2): Similarly, within-aisle blocking ($\beta_9 = 0.058, p < 0.01$) results in an estimated ($e^{0.058} - 1$), or 6.0% increase in task performance time. This implies that order pickers who encounter another picker blocking their path in the aisle require additional time to complete their tasks because they must either wait or manoeuvre around the obstruction.

These main effects provide a baseline understanding of how pick-column and within-aisle blocking influence task performance time across the full sample. To assess how AGV assistance modifies these effects, we turn to Model (3), which incorporates the interaction terms between AGV assistance and each type of picker blocking.

Interaction term 1 (*AGV assistance × pick-column blocking*): The interaction effect between AGV assistance and pick-column blocking ($\beta_{10} = -0.035, p < 0.01$) indicates that AGV assistance reduces the additional time required to complete a task because of pick-column blocking. The interaction coefficient represents the isolated effect and indicates that AGV-assisted pickers experience approximately 3.4% less delay from pick-column blocking compared to pickers operating with prior technology.

The total effect of pick-column blocking for AGV-assisted order pickers is determined by combining the main effect of pick-column blocking ($\beta_8 = 0.098, p < 0.01$) with the interaction term ($\beta_{10} = -0.035, p < 0.01$), resulting in $\beta_8 + \beta_{10} = 0.098 - 0.035 = 0.063$. This corresponds to an approximate 6.5% increase in task performance time as a result of pick-column blocking for AGV-assisted pickers ($e^{0.063} - 1$), compared to 10.3% for pickers operating with prior technology ($e^{0.098} - 1$). The isolated interaction effect alone indicates that AGV assistance reduces the additional delay from pick-column blocking by approximately 3.4% ($e^{-0.035} - 1$) relative to pickers operating with the prior generation of technology. These results indicate that while pick-column blocking continues to increase task performance time, AGV support partially offsets its impact.

Interaction term 2 (*AGV assistance × Within-aisle blocking*): The interaction between AGV assistance and within-aisle blocking ($\beta_{11} = -0.021, p < 0.01$) indicates that compared to picking with prior technology, having AGV support reduces the extension of task time resulting from within-aisle blocking. The isolated interaction coefficient shows that those with AGV assistance experience approximately 2.1% less delay from within-aisle blocking than manual pickers ($e^{-0.021} - 1 \approx -0.021$).

The total effect of within-aisle blocking for AGV-assisted order pickers is determined by combining the main effect of within-aisle blocking ($\beta_9 = 0.061, p < 0.01$) with the interaction term: $\beta_9 + \beta_{11} = 0.061 - 0.021 = 0.040$. This corresponds to an approximate 4.1% increase in task performance time for AGV-assisted pickers ($e^{0.040} - 1 \approx 0.041$), relative to 6.3% for pickers operating with prior technology ($e^{0.061} - 1 \approx 0.063$). These results indicate that while within-aisle blocking continues to increase task performance time, AGV assistance support partially offsets the adverse effect by enabling pickers to navigate congested aisles more efficiently.

5.2. Robustness checks

We confirm that our main findings are reliable and not dependent on specific model assumptions by running several robustness and sensitivity checks. These test whether the results remain stable when we change the statistical approach or relax certain assumptions. The main mixed-effects regression model already accounts for a hierarchical data structure and correlated observations by including a random intercept for each picker–time combination. However, the model also relies on several assumptions, such as normally distributed residuals and homoscedastic errors, that we explicitly relax in the robustness analyses to verify our conclusions. Each check therefore targets a distinct statistical assumption: unobserved individual heterogeneity (fixed effects), distributional form (AFTM), and error variance (heteroscedasticity).

First, we estimate a fixed-effects model that controls for all time-invariant characteristics at the picker level, such as experience, baseline speed, or individual working style. This approach focuses exclusively on within-picker variation over time and thus removes all stable differences across individuals. Using a fixed-effects specification serves as a robustness check because it tests whether the main results depend on unobserved, time-invariant individual differences. If the effects are consistent across the fixed and mixed-effects models, we can be confident that the estimated relationships are not driven by cross-sectional heterogeneity, such as differences in skill or fatigue resistance across pickers. In this sense, the fixed-effects model provides a conservative benchmark: it isolates the variation within a picker and ensures that the observed relationships reflect genuine within-individual dynamics rather than between-individual bias.

Second, we apply an AFTM as an alternative approach to the analysis of task durations and verify the robustness of our results against distributional assumptions. Our main analysis employs a mixed-effects model on log-transformed task performance time, which assumes that the residual variation around the mean is approximately symmetric. However, task performance data are often right-skewed and may follow a specific statistical distribution. The AFTM framework models this explicitly by assuming a parametric form for task durations, in our case, a log-normal distribution, which directly relates covariates to the expected completion time. This approach is well-suited for order picking data because it treats each task as a ‘time-to-completion’ process, allowing us to interpret effects in terms of acceleration or deceleration of that process (Loske et al., 2024b). By comparing the AFTM estimates with those of the mixed-effects regression, we can check whether these remain stable when we model task durations to explicitly account for their probabilistic structure. If the two approaches yield consistent effects, it increases our confidence that our conclusions are not sensitive to the chosen modelling framework but reflect an underlying behavioural mechanism that persists across statistical specifications.

Third, we conduct a heteroscedasticity diagnostic and use the Breusch–Pagan test to examine whether the variance of residuals (the unexplained part of task performance time) remains constant across observations. In many real-world datasets, the amount of unexplained variation can differ systematically across situations or individuals. For example, some pickers may vary in their task times more than others, or performance might fluctuate more strongly under certain congestion levels. This phenomenon, known as heteroscedasticity, does not bias the estimated coefficients themselves, but can result in reported standard errors that are either too small or too large, leading to misleading significance levels.

We address this by formally testing for heteroscedasticity using the Breusch–Pagan test, which assesses whether the residual variance depends on the independent variables. We conduct this diagnostic test as part of our robustness checks rather than in the main model, because the mixed-effects framework already accounts for some structured variation (such as differences between pickers or time blocks) through its random intercepts. The test, therefore, helps to verify whether any remaining, unmodelled heteroscedasticity persists beyond what is captured by the random effects. After detecting non-constant variance, we re-estimate all models using robust standard errors clustered at the picker level. This adjustment accommodates heteroscedasticity and within-individual correlation, producing more reliable standard errors and significance tests. The clustered approach ensures that repeated observations from the same picker, which are naturally dependent, do not distort inference. A comparison of the results of the cluster-robust models and our main estimates shows that our key conclusions are unaffected by unequal error variance or correlated residuals within individuals.

Table 4
Fixed-effects model with picker-clustered robust standard errors.

	Dependent variable: Log(Task performance time)		
	FE Model (1)	FE Model (2)	FE Model (3)
Main effects			
Pick-column blocking		0.090 (0.002) $p < 0.01$	0.097 (0.002) $p < 0.01$
Within-aisle blocking		0.057 (0.002) $p < 0.01$	0.060 (0.002) $p < 0.01$
Interaction terms			
AGV assistance × Pick-column blocking			−0.032 (0.005) $p < 0.01$
AGV assistance × Within-aisle blocking			−0.017 (0.005) $p < 0.01$
Control variables			
Product weight	0.002 (0.0001) $p < 0.01$	0.002 (0.0001) $p < 0.01$	0.002 (0.0001) $p < 0.01$
Product volume	0.0005 (0.00004) $p < 0.01$	0.0005 (0.00004) $p < 0.01$	0.0005 (0.00004) $p < 0.01$
Travel distance	0.001 (0.0002) $p < 0.01$	0.001 (0.0002) $p < 0.01$	0.001 (0.0002) $p < 0.01$
Batch position	0.004 (0.0001) $p < 0.01$	0.004 (0.0001) $p < 0.01$	0.004 (0.0001) $p < 0.01$
Products per batch position	0.030 (0.0002) $p < 0.01$	0.030 (0.0002) $p < 0.01$	0.030 (0.0002) $p < 0.01$
Total pickers in the aisle	0.001 (0.0004) $p = 0.620$	−0.0001 (0.0004) $p = 0.519$	−0.0001 (0.0004) $p = 0.505$
AGV assistance	−0.229 (0.069) $p < 0.01$	−0.238 (0.072) $p < 0.01$	−0.214 (0.055) $p < 0.01$
Pickers	205	205	205
Observations	490,398	490,398	490,398
R^2_c	0.112	0.120	0.120
F Statistic	10,339***	8,323***	6,668***

Note: Clustered robust standard errors in parentheses. P-values below coefficients; small values as $p < 0.01$.

Overall, the robustness analyses provide strong support for the stability of our results, confirming that the key relationships hold regardless of the chosen modelling approach or distributional assumptions.

5.2.1. *Fixed-effects model*

As a further robustness test, we estimate a fixed-effects model using within-transformation, a technique that controls for all time-invariant, picker-specific characteristics. This approach focuses on within-picker variation and effectively absorbs any unobserved heterogeneity across pickers, such as individual skills, experience levels, or physical condition, that do not change over time. Unlike the mixed-effects specification, the fixed-effects model does not model between-picker differences directly. Rather, it removes their influence from the estimation by design (Borenstein et al., 2010).

We include the same independent and control variables as in the main model to ensure comparability. Although the fixed-effects model does not incorporate random effects, it is well-suited to isolate the impact of time-varying predictors on task performance.

The results are summarised in Table 4.

The results of the fixed-effects models support the robustness of our main findings. The estimated coefficients for both pick-column and within-aisle blocking remain positive and statistically significant, and with magnitudes comparable to those in the hierarchical, mixed-effects models. This consistency in direction and effect size suggests that the relationship between congestion effects and task performance time is not an artefact of the model structure.

Moreover, in the fixed-effect Model (3), the interaction terms between AGV assistance and the blocking variables remain negative and significant, confirming that picking with the new technology moderates the negative effects of blocking. Our conclusions thus hold even when unobserved, time-invariant picker-specific characteristics are accounted for using a fixed effects approach. Importantly, although fixed-effects models do not capture between-picker variation, the fact that the results align closely with those of the mixed-effects models demonstrates that our findings are robust to alternative specifications and do not rely on variation across individuals.

5.2.2. *Accelerated failure time model*

We further validate our findings by estimating an AFTM with a log-normal distribution. AFTM models are commonly used to model time-to-event data and provide an alternative to log-linear regression when analysing task performance time (Loske et al., 2024b). Unlike linear regression, which models the mean of the log-transformed outcome, the AFTM directly models the time until a task is completed, assuming a specific distributional form for the error term.

The AFTM results, shown in Table 5, are highly consistent with our main model and the fixed effects estimation. In Model (2), both pick-column blocking and within-aisle blocking are associated with a significant increase in task performance time. In Model (3), the interaction terms between AGV assistance and each blocking variable are negative and significant, indicating that AGV assistance mitigates the impact of congestion effects, as observed in our previous models.

The direction, magnitude, and statistical significance of the coefficients largely align with the results from the mixed- and fixed-effects models. This strengthens confidence in our conclusions by demonstrating that the key relationships remain stable even when using a different modelling framework that is specifically designed to analyse duration-based outcomes.

5.2.3. *Breusch–Pagan test*

In regression analysis, a key assumption of classical linear models is homoscedasticity, meaning that the variance of residuals, defined as the unexplained portion of the dependent variable, remains constant across all observations (Breusch and Pagan, 1979). If this assumption is violated, the estimated coefficients remain unbiased, but the standard

Table 5
Accelerated failure time model (log-normal)

	Dependent variable: Log(Task performance time)		
	AFTM Model (1)	AFTM Model (2)	AFTM Model (3)
Main effects			
Pick-column blocking		0.074 (0.002) $p < 0.01$	0.081 (0.002) $p < 0.01$
Within-aisle blocking		0.030 (0.002) $p < 0.01$	0.033 (0.002) $p < 0.01$
Interaction terms			
AGV assistance × Pick-column blocking			−0.031 (0.005) $p < 0.01$
AGV assistance × Within-aisle blocking			−0.016 (0.005) $p < 0.01$
Control variables			
Product weight	0.002 (0.0001) $p < 0.01$	0.002 (0.0001) $p < 0.01$	0.002 (0.0001) $p < 0.01$
Product volume	0.001 (0.00004) $p < 0.01$	0.001 (0.00004) $p < 0.01$	0.001 (0.00004) $p < 0.01$
Travel distance	0.001 (0.0002) $p < 0.01$	0.001 (0.0002) $p < 0.01$	0.001 (0.0002) $p < 0.01$
Picks	0.030 (0.0002) $p < 0.01$	0.030 (0.0002) $p < 0.01$	0.030 (0.0002) $p < 0.01$
Total pickers in aisle	0.001 (0.0002) $p < 0.01$	0.0002 (0.0002) $p = 0.338$	0.0002 (0.0002) $p = 0.354$
Batch position	0.005 (0.0001) $p < 0.01$	0.005 (0.0001) $p < 0.01$	0.005 (0.0001) $p < 0.01$
AGV assistance	−0.229 (0.002) $p < 0.01$	−0.238 (0.002) $p < 0.01$	−0.214 (0.004) $p < 0.01$
Pickers	205	205	205
Observations	490,398	490,398	490,398
Log Likelihood	$-1,762,952$	$-1,761,848$	$-1,761,814$
χ^2	65,161***	67,369***	67,438***

Note: Clustered robust standard errors in parentheses. P-values below coefficients; small values as $p < 0.01$.

errors become unreliable. This can, in turn, lead to incorrect inference, such as misleading p-values and confidence intervals.

We test for the presence of heteroscedasticity in our data using the Breusch–Pagan test, a widely used diagnostic introduced by Breusch and Pagan (1979) to examine whether the variance of the residuals from a regression model systematically depends on one or more of the independent variables. Specifically, it regresses the squared residuals from the main model on the set of explanatory variables and tests whether their explanatory power is significantly different from zero.

Formally, the null hypotheses (H_0) of the Breusch–Pagan test is that there is constant variance of the residuals, known as homoscedasticity. The alternative hypothesis (H_A) is that the variance of the residuals depends on the predictors, indicating the presence of heteroscedasticity. In our case, the Breusch–Pagan test strongly rejects the null hypothesis (test statistic > 13,000; $p < 0.001$), providing robust evidence of heteroscedasticity in the residuals of the ordinary least-squares model.

Given this result, we proceed to correct for heteroscedasticity and within-group correlation by estimating the model with robust standard errors clustered at the picker level. This adjusts the estimated variance–covariance matrix to allow for non-constant error variance and correlated residuals within picker clusters; this correction is essential in panel or grouped data settings like ours.

The regression results with cluster-robust standard errors are shown in Table 6.

As evident from the table, the coefficients of the main variables of interest remain stable in sign and significance. This consistency across estimation strategies further substantiates our findings. Moreover, the Breusch–Pagan test for heteroscedasticity provides additional support for the main model's results and reinforces our conclusions. The test's rejection of the null hypothesis of homoscedasticity suggests that correcting for heteroscedasticity and within-group correlation by using robust standard errors clustered at the picker level is an important adjustment that ensures more reliable inferences.

6. Discussion and conclusion

6.1. Discussion of results

Prior research has explored the causes and consequences of picker blocking, highlighting the role of storage assignment, routing policies, and congestion management in mitigating its negative effects on order-picking performance (Bahrami et al., 2017; Elbert et al., 2015a; Franzke et al., 2017; Löffler et al., 2021). Studies suggest that class-based storage and inefficient routing strategies can intensify blocking, whereas optimised routing approaches, such as S-shaped and return routing, help alleviate congestion (Pan et al., 2012; Hong et al., 2012). Research on hybrid order-picking systems indicates that robots can reduce human-to-human blocking, though improper synchronisation of human pickers and robots may introduce new delays (Winkelhaus et al., 2022). Empirical findings suggest that moderate AGV integration (below 20% of total pickers in the aisle) helps distribute workloads and reduce in-aisle blocking. However, excessive AGVs may create rigid movement patterns that increase congestion, particularly in high-density warehouse environments (Koreis et al., 2025b).

Our study extends this body of literature by empirically analysing how pick-column and within-aisle blocking affect task performance time in a shared warehouse aisle where order pickers using prior- and new-generation technologies operate simultaneously. We further examined how AGV assistance influences congestion patterns.

We find that AGV assistance mitigates the negative impact of pick-column and within-aisle blocking, offering a performance advantage over prior-generation technology. This effect can be explained by the distinct movement patterns allowed by AGVs, which reduce unnecessary stopping, dismounting, and inefficient travel paths.

In the case of pick-column blocking, AGV assistance allows pickers to maintain a continuous flow of movement. Working with prior-generation technology, the order picker must stop, dismount, and manoeuvre the industrial truck when a pick location is blocked by

Table 6
OLS model with picker-clustered robust standard errors.

	Dependent variable: Log(Task performance time)		
	OLS Model (1)	OLS Model (2)	OLS Model (3)
Main effects			
Pick-column blocking		0.074 (0.008) $p < 0.01$	0.081 (0.007) $p < 0.01$
Within-aisle blocking		0.030 (0.006) $p < 0.01$	0.033 (0.007) $p < 0.01$
Interaction terms			
AGV assistance × Pick-column blocking			−0.031 (0.019) $p = 0.098$
AGV assistance × Within-aisle blocking			−0.016 (0.014) $p = 0.044$
Control variables			
Product weight	0.002 (0.001) $p = 0.075$	0.002 (0.001) $p = 0.070$	0.002 (0.001) $p = 0.070$
Product volume	0.001 (0.0005) $p = 0.075$	0.001 (0.0005) $p = 0.105$	0.001 (0.0005) $p = 0.101$
Travel distance	0.001 (0.001) $p = 0.489$	0.001 (0.001) $p = 0.431$	0.001 (0.001) $p = 0.430$
Picks	0.030 (0.002) $p < 0.01$	0.030 (0.002) $p < 0.01$	0.030 (0.002) $p < 0.01$
Total pickers in aisle	0.001 (0.0004) $p < 0.01$	0.0002 (0.0004) $p = 0.609$	0.0002 (0.0004) $p = 0.621$
Batch position	0.005 (0.001) $p < 0.01$	0.005 (0.001) $p < 0.01$	0.005 (0.001) $p < 0.01$
AGV assistance	−0.229 (0.069) $p < 0.01$	−0.238 (0.072) $p < 0.01$	−0.214 (0.055) $p < 0.01$
Observations	490,398	490,398	490,398
R_c^2	0.124	0.128	0.128
F Statistic	9,955***	8,024***	6,572***

Note: Clustered robust standard errors in parentheses. P-values below coefficients; small values as $p < 0.01$.

another picker, leading to delays. With the new-generation technology, the picker can walk directly to the blocked pick location and retrieve the required products, with the AGV automatically halting behind the obstruction. Once the picker completes the pick event and moves away, the AGV autonomously advances to the now available pick location. This eliminates unnecessary stopping, dismounting, and backtracking, enabling a smoother and more efficient picking process. The ability of AGVs to seamlessly integrate with the picker's movement reduces wasted motion and improves task performance times. However, workers may initially adjust their spacing behaviour in response to AGVs to maintain a particular IPD; humans tend to subconsciously regulate their proximity to people and objects in shared spaces (Gifford, 1983). Over time, as pickers become accustomed to AGVs' movement patterns, these adjustments may stabilise, leading to more natural navigation behaviour.

This behavioural stabilisation can also be interpreted through the lens of EVT, according to which, individuals continuously form expectations about others' movements and reactions in shared workspaces. When these expectations are violated, for example, by unexpected vehicle motion or irregular pacing, temporary cognitive disruptions and hesitation may result, reducing task fluency. In contrast, AGVs exhibit highly predictable and consistent patterns of movement, maintaining a constant following distance, stopping automatically when the picker stops, and resuming smoothly once space becomes available. This predictability reduces expectancy violations and lowers cognitive load, enabling pickers to anticipate AGV behaviour with greater confidence. The overall movement flow becomes more stable and less fragmented as a result, even during temporary blocking situations. Over time, this reinforcement of predictable movement sequences likely supports the smoother workflow observed for AGV-assisted pickers during pick-column blocking events.

For within-aisle blocking, AGV assistance offers two key advantages. First, when batch positions are in close proximity, AGV-assisted order pickers can walk past the blocking picker, with the AGV catching up once the obstruction clears. Second, AGVs can automatically navigate around blockages, reducing the need for manual repositioning and enabling a more fluid picking process. These advantages help AGV-assisted pickers maintain their productivity even in congested aisles, reinforcing the performance gains observed in our empirical analysis. EVT suggests that AGV stops or repositioning that deviate from a picker's expectations may momentarily disrupt workflow (Perry et al., 2015). As workers develop a mental model of AGV behaviour, this effect may diminish, highlighting the importance of predictability in human–AGV collaboration.

In simple terms, EVT points to a straightforward mechanism: if the AGV moves predictably, pickers know what will happen next. They hesitate less, they are required to engage in fewer on-the-spot negotiations about who goes first, and they avoid small corrective movements. In our data, this appears as fewer short pauses in the overlap window and a clearly smaller within-aisle blocking penalty. With experience, pickers adopt simple rules (for example, maintaining a one- to two-location spacing or stepping aside briefly without backtracking), further stabilising the flow in congested aisles.

6.2. Warehouse management implications

Our findings offer valuable managerial insights for effectively incorporating AGVs into order picking environments, particularly where a complete transition to AGV fleets remains impractical or cost-prohibitive.

First, managers should treat picker blocking as a critical performance driver. Pick-column blocking and within-aisle blocking increase average task performance time by 9.4% and 6.0%, respectively. Even short periods of co-location at the same or adjacent pick locations, or short headway conflicts on the same side of the aisle, create systematic delays. Warehouse managers should establish specific blocking indicators within the warehouse management system and integrate them into daily operational reporting. These indicators should track the frequency of blocking, its duration, and the location where it occurs most frequently.

In practice, managers can measure the number of blocking events per batch, distinguishing between pick-column blocking and within-aisle blocking, and record the average additional time caused by each event. Monitoring the proportion of pick events within a batch affected by picker blocking helps identify structural congestion rather than being limited to isolated cases. Once the blocking incidence in a specific aisle or pick column repeatedly exceeds 20%–30% or the average delay per blocked event surpasses 5–7 s, the affected areas should be flagged as congestion hotspots in the WMS. These can then be visualised on a digital warehouse map or heatmap that highlights congestion intensity across aisles and time intervals. Managers and team leaders can then see, at a glance, which areas consistently slow down performance. By integrating these metrics into the daily warehouse control dashboard, supervisors can respond in real time, for example, by reducing the number of pickers working simultaneously in a hotspot aisle, temporarily re-routing pickers to alternative zones, or adjusting batch releases to smooth traffic peaks. Over time, patterns of recurring congestion should guide structural layout or slotting adjustments to ensure that high-turnover or bulky products are distributed more evenly across pick columns or aisle sides. Tracking progress on these indicators on a weekly basis enables continuous improvement, helps sustain picker productivity, and reduces unnecessary idle time across shifts.

Second, warehouse managers should deploy AGV assistance strategically rather than uniformly across all aisles or shifts. Our results show that AGV assistance reduces the additional delay from pick-column blocking by 3.4% and from within-aisle blocking by 2.1% compared to when the prior-generation technology is employed. This means AGVs yield the greatest benefits in high-congestion zones, where human pickers frequently interfere with each other's routes or compete for the same pick locations. Managers should use historical WMS data to pinpoint where blocking is most persistent, typically in aisles with high SKU turnover, dense pick sequences, or frequent two-sided access. In these hotspots, AGVs should be scheduled to accompany pickers during the most congested periods, such as the peak morning or late-afternoon waves. Rather than allocating AGVs evenly across shifts, managers can take a dynamic approach: more AGV-assisted pickers can be assigned to dense, high-traffic aisles, with conventional vehicles relied on in low-density areas. This targeted deployment ensures that AGV capacity is used where the performance penalty of blocking is greatest.

AGV deployment rules can also be embedded directly into WMS settings. For example, AGVs could be automatically assigned to batches with overlapping pick positions, high product density, or routes that have historically been prone to congestion. Managers can periodically review heatmaps of congestion and adjust AGV schedules accordingly. This combination of data-driven hotspot detection and adaptive deployment planning helps maintain smooth traffic flow and maximises the return on AGV investment without increasing total fleet size.

We substantiate these managerial implications by adding a preliminary ROI analysis. This illustrates the potential economic benefits of AGV-assisted order picking in warehouse operations by translating the observed performance improvements into an approximate economic assessment at the level of a single AGV-assisted order picker. Specifically, we use the empirically derived time change of AGVs relative to prior technology, expressed as follows:

$$\%\Delta T_{\mathrm{AGV}} = \exp(-0.356 - 0.035 r_{\mathrm{pc}} - 0.021 r_{\mathrm{wa}}) - 1, \tag{9}$$

where r_{pc} and r_{wa} denote the share of pick-column blocking and within-aisle blocking events in the respective scenario. The coefficients in Eq. (9) are taken directly from the interaction terms estimated in Section 5.1 (Model 3 in Table 3), with −0.035 for pick-column blocking and −0.021 for within-aisle blocking. The intercept (−0.356) represents the average impact of AGV assistance on task performance time under mean operating conditions, corresponding to an overall reduction of 29.95% ($e^{-0.356} - 1$) in task performance time relative to the prior-generation technology. This formulation captures the average performance improvement of AGV-assisted order picking and its mitigating effect on congestion-related blocking times. The resulting time advantage represents the total percentage savings in task performance time compared to picking using the prior generation. For each scenario, we assume a typical shift length of 7.5 h, and translate the corresponding time saving into proportional labour cost reductions.

Table 7
ROI sensitivity scenarios per AGV unit.

Scenario	Country	Hours	Savings (%)	Hourly wage (EUR)	EUR saved/month	Payback (months)
S1	Germany	7.5	30.7%	17.65	€853	29.3
S2	Germany	7.5	31.4%	17.65	€873	28.6
S3	Germany	7.5	32.0%	17.65	€889	28.1
S4	Germany	7.5	32.4%	17.65	€900	27.8
S5	Luxembourg	7.5	31.8%	15.12	€757	33.0
S6	Netherlands	7.5	31.8%	14.06	€704	35.5
S7	France	7.5	31.8%	11.88	€595	42.0
S8	Spain	7.5	31.8%	8.37	€419	59.7

For Scenarios 1–4, we vary the assumed mean picker blocking shares to reflect different congestion levels (r_{pc} = 0.15–0.55, r_{wa} = 0.25–0.75). For Scenarios 5–8, we apply the empirical mean values from our descriptive statistics in Table 1 ($r_{\mathrm{pc}} = 0.37$, $r_{\mathrm{wa}} = 0.66$) to represent typical operating conditions across European warehouses.

Using this approach, the first set of scenarios captures performance sensitivity to congestion variation, and the second set isolates the effect of wage differences across countries under average blocking conditions. The wage assumptions for Scenarios 5–8 are based on the statutory minimum wages reported for 2025 across EU member states (Statista Research Department, 2025); for Germany, the approximate hourly wage level of the warehouse under investigation is applied to ensure realistic comparability with the empirical setting.

Based on the estimated performance improvements, the corresponding time savings per shift are translated into a proportional reduction in total labour hours required to complete the same workload. This reduction directly reflects the economic value of AGV assistance, as fewer working hours are needed to achieve the same output. We approximate the financial impact of this by converting the saved time into monetary terms using the respective country-specific hourly wages and an average of 21 working days per month, resulting in the monthly savings reported in Table 7. Assuming an investment of EUR 25,000 per AGV, these savings are accumulated over time to determine the payback period, defined as the point at which cumulative savings offset the initial investment. Fig. 3 illustrates the resulting ROI.

The resulting ROI reveal that Scenarios S1–S4, which vary in average blocking intensity and thus in realised time savings, exhibit only minor differences in payback duration. Across these scenarios, the payback period ranges between 27 and 30 months, indicating that moderate variations in congestion have a relatively small impact on overall investment recovery time. In contrast, Scenarios 5–8 show more pronounced differences across European countries due to wage differences. Here, the payback period extends from roughly 33 months in Luxembourg to 59 months in Spain, reflecting the strong sensitivity of the ROI to local labour cost structures. These results highlight that while the productivity gains of AGV assistance are robust across operational conditions, the economic attractiveness of such investments largely depends on the prevailing wage environment.

6.3. Contributions to theory

Our study makes several contributions to the literature on order-picking performance and automation in warehouse operations. First,

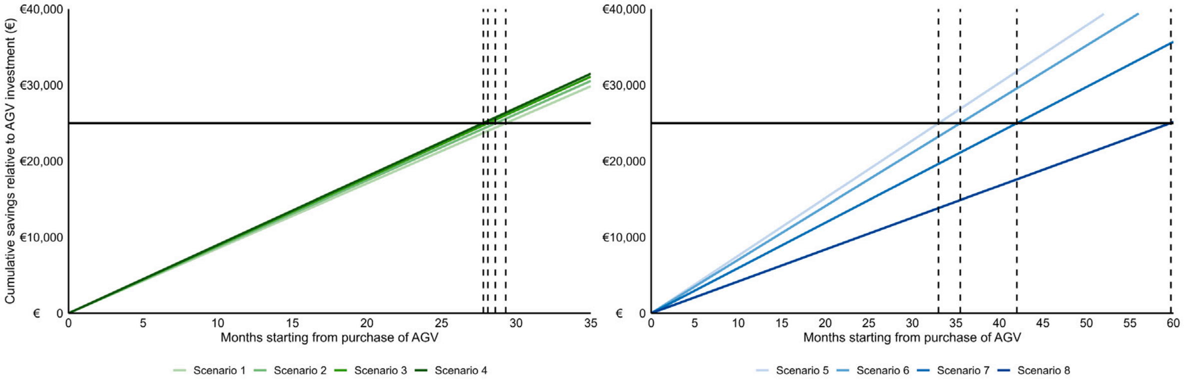

Fig. 3. ROI scenarios for one AGV-assisted order picker.

it empirically demonstrates how picker blocking, specifically pick-column and within-aisle blocking, affects task performance time at the individual picker level. While previous research has explored congestion effects in order picking, our study extends this understanding by quantifying the direct impact of blocking on operational performance in a shared workspace where order pickers operate with prior and new-generation technologies simultaneously. Future research could extend this quantitative insight by verifying and even applying this calculation to other order picking and warehouse logistics settings.

Second, we contribute to the growing research on human–robot collaboration in warehouse environments by showing that AGV assistance mitigates the negative effects of picker blocking. Our findings show that AGVs allow pickers to maintain a more continuous workflow by reducing unnecessary stopping, dismounting, and repositioning. We provide empirical support for the argument that partial automation can improve warehouse performance, even in order-picking environments where complete AGV fleets are not yet feasible. This is important for neighbouring theoretical fields and models, for example, the relevant investment case calculations for AGV and automation technology in warehousing.

Third, our study offers important insights and has implications for warehouse optimisation in terms of how AGV assistance interacts with congestion patterns. The insights from our research suggest that AGVs should not be seen as mere transport aids but as tools that can actively shape movement dynamics and strategies to resolve congestion. Understanding these effects can help managers refine their order assignment, routing policies, and warehouse layouts to maximise the performance of AGV-assisted operations.

This is also an important point for theoretical discourse, since in virtually all existing models on warehouse issues like layout or routing, AGV and automation issues are only understood as a single-objective tool to increase speed and performance. The newly discovered coordination effect has yet to be included in relevant theoretical models in this area. There might be even greater insights available when these findings are read alongside the grounding theory approaches in psychology or HR management. The findings regarding the perception of personal distances can be included in theory building and modelling, for example, in defining aisle-width norms and regulations in the future; for example, could these be made narrower or wider with AGVs integrated as a share of the support technology for order pickers?

Finally, the insight provided into related concepts, such as IPD is also relevant for many logistical and operational contexts and theories. The discussed elements of social norms, personal comfort or safety perceptions, or situational constraints (Mirlisenna et al., 2024) are thus of continued interest for the development of theory in many areas of logistics and operations, including transportation, contract logistics or service logistics. EVT adds a complementary perspective here. It suggests that predictable agent behaviour reduces the element of surprise and hesitation in close interactions, which offers a simple explanation for why AGV-assisted order pickers experience fewer short disruptions in congested spaces. The value of this study in terms of theory development is complemented by the interdisciplinary perspective on the human factor and detailed analyses in this regard (e.g. Corbett, 2023, Corbett et al., 2025, Loske et al., 2024a). Future research and theoretical discourse are highly warranted in this field as individual worker characteristics, including perception and motivation, are crucial to further logistical optimisation, aided by the increasing capabilities of data gathering and data processing.

6.4. Limitations

Despite these contributions, our study has certain limitations. Our findings are based on data from a single warehouse environment, which may limit the generalisability of our results to other settings with different aisle widths, storage configurations, or order-picking strategies. Warehouse layouts, product mix, and traffic patterns vary significantly across industries. While our findings provide a strong empirical foundation, further studies in diverse operational contexts are needed to fully validate our conclusions.

Our study also relies on an archival dataset derived from the WMS, which, while offering rich and detailed real-world data, also has inherent constraints. The dataset does not capture qualitative factors such as individual picker behaviour, real-time decision-making, or adaptive strategies to mitigate congestion. Furthermore, WMS data records pick events as they are logged, meaning that they do not explicitly account for micro-level movement dynamics, such as minor hesitations, adjustments, or informal communication between pickers. Integrating sensor-based tracking or real-time observational studies could complement our approach and offer deeper insights into how pickers interact with AGVs in blocking situations.

Another limitation is the potential between-picker variability across the two groups (order picking with old technology vs. new-generation technology). While our model includes a random intercept for each picker, which controls for baseline differences in individual task performance time, this does not fully eliminate the possibility that observed differences in picker-blocking effects are partially influenced by differences in picker ability rather than the technology itself. Specifically, if more adaptive pickers are systematically overrepresented in the AGV-assisted group, part of the positive effect of AGV assistance on mitigating picker blocking might actually be attributable to differences in individual picker performance. The ICC analysis shows that 10.1% of the variance in task performance time can be attributed to differences between individual pickers, indicating that individual variability plays a non-negligible role in explaining performance outcomes.

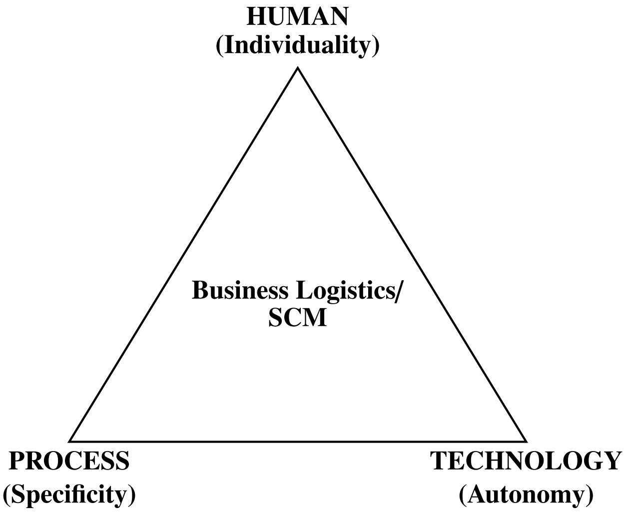

Fig. 4. Triangular model of human individuality, technology autonomy, and process specificity in business logistics.

6.5. Avenues for future research

Beyond the insights into the operational benefits of AGV-assisted order picking, our findings also highlight several areas that warrant further research, depicted in a conceptual triangular approach in Fig. 4. With respect to the technology angle in our analytical triangle, further research should examine the scalability of AGV assistance in warehouse environments with varying levels of congestion and different storage configurations. This includes the increased autonomy of technology solutions, as represented here by AGV picker assistance, but could extend to many other automated and autonomous technologies in logistics operations in the future. While our findings suggest that AGVs reduce the negative impact of picker blocking, the extent to which these benefits hold in high-density settings or under different storage assignment strategies remains an open question. Further research is thus warranted regarding this process-specificity dimension. Simulation-based approaches could help model AGV-human interactions in warehouses with different aisle widths, order-clustering patterns, and levels of automation, providing deeper, relevant insights into optimal deployment strategies.

Future research could also explore the application to AGV-assisted order picking of platooning and synchronised AGV coordination, concepts developed for truck convoys in transportation logistics and cycle time optimisation in manufacturing. In transportation, platooning allows multiple trucks to travel in coordinated formations and adjust their speeds dynamically through vehicle-to-vehicle communication to optimise traffic flow and reduce congestion (Bergenhem et al., 2012). Similarly, in manufacturing, flow optimisation and cycle time coordination ensure that different production steps are precisely aligned to maintain an optimal workflow and prevent bottlenecks (Zhang et al., 2009). This idea mainly concerns the technology side and its link to the process side of the triangle (see Fig. 4).

Building on these ideas, future work could test whether applying these principles to AGV-assisted order picking would allow synchronised movement strategies that minimise congestion and improve order-picking performance. AGVs could be dynamically coordinated to prevent bottlenecks. If a picker is delayed at a pick location, AGVs could adjust their speed accordingly, preventing unnecessary stops that contribute to aisle congestion. Likewise, an AGV that encounters a blocked path could reroute proactively rather than reactively, reducing the impact of obstructions. In high-density environments, AGVs could be orchestrated, similarly to identical production line pacing, ensuring steady material and picker movement, reducing congestion, and optimising the interaction with human pickers. Notably, such concepts may only now be feasible due to the technological characteristics of AGVs, for example, their ability to communicate and autonomously maintain fixed distances and speed-sequence norms inside a warehouse or single aisle (with options to adjust this to aisle and product characteristics as well as make dynamic adjustments).

Beyond simple movement synchronisation, future research could also investigate whether vehicle-to-vehicle communication could be deployed to allow AGVs to share real-time congestion data and coordinate their speeds dynamically. If an AGV detects congestion ahead, it could autonomously reroute or adjust its pace to avoid exacerbating the blockage. This adaptive traffic-management approach could substantially mitigate the negative effects of picker blocking for more fluid and coordinated warehouse operations in which AGVs and human pickers operate as an integrated system rather than as independent entities (see Fig. 4). This line of inquiry could be further informed by perspectives from psychology and HR management regarding workers' safety and distance perceptions, for example, in defining the exact distance between platooned or synchronised movements of AGVs in an aisle.

Future research should examine whether the challenges of congestion, movement coordination, and human–robot interaction observed in warehouse logistics also arise in other automated material-handling and intra-logistics applications. In manufacturing environments, where AGVs frequently transport materials between production stations, congestion at key supply points may cause inefficiencies that are similar to picker blocking in warehouses. By applying synchronised AGV coordination strategies within the production logistics domain, for example, adaptive pacing and dynamic speed adjustments, future studies could test whether manufacturers can reduce material transport delays and ensure a smoother flow (Xia et al., 2020).

Another domain that warrants investigation is healthcare logistics. AGVs are increasingly deployed to transport medical supplies, laboratory samples, and equipment, for example, within hospitals (Benzidia et al., 2019). Because hospital corridors often experience high traffic density, similar to warehouse aisles, researchers could evaluate whether adaptive AGV coordination strategies might ensure uninterrupted supply chains, particularly in critical care settings (Aziez et al., 2022). Airports have also begun utilising AGV-assisted baggage handling and autonomous ground support vehicles; bottlenecks in baggage transfer zones or aircraft servicing could be mitigated through such strategies and merit systematic study (Shen et al., 2020).

The growing trend towards autonomous last-mile delivery presents another opportunity for external validation (Alverhed et al., 2024). Urban environments, where sidewalk delivery robots and autonomous transport vehicles are increasingly deployed, present unique routing and congestion challenges. Future work could investigate whether insights from warehouse-based AGV congestion management could produce better fleet coordination strategies and lead to smoother last-mile delivery flows in densely populated areas.

Another promising direction for research is refining the movement logic of AGVs to enhance congestion avoidance. Our study suggests that AGVs mitigate picker blocking by enabling more efficient movement flows. However, current AGV path-planning strategies remain rigid relative to human decision-making. Future research could investigate how dynamic AGV routing algorithms, real-time congestion detection, or adaptive movement patterns could further optimise AGV-assisted order picking in shared warehouse spaces. Again, a research setting dedicated to process specificity, as shown in Fig. 4, is crucial for external validity in making management decisions, as many insights may only hold for a setting that is defined in great detail.

While our study focuses on performance outcomes, future research should also consider human factors and individuality, as represented in Fig. 4, including ergonomic implications and worker well-being in AGV-assisted order picking. The reduction in unnecessary stopping and repositioning efforts may reduce physical strain, but further empirical studies are needed to assess the long-term effects on effective workload, human worker fatigue, stress, and job satisfaction. Integrating biomechanical assessments or physiological monitoring into future research could provide a more comprehensive understanding of how AGVs influence performance and worker well-being, including the notion of individuality presented here. The effects of human perception and psychological transmission mechanisms may be highly individual and therefore difficult to grasp for logistics research and management alike.

Finally, our study controls for between- and within-picker variability, but does not capture potential systematic differences in adaptability between pickers operating with prior and new technologies. Future research should explore alternative experimental designs. For example, cross-over studies, in which the same order pickers perform tasks with and without AGV assistance, would allow for a within-subject comparison that eliminates individual variability as a confounding factor.

6.6. Conclusion

This study is a potential cornerstone for future research into the interaction of technology assistance systems with increased autonomy, mixed-technology settings, and the individual characteristics of human workers. The outlined triangle of logistics process specificity, technological autonomy, and human individuality (see Fig. 4) offers a framework for further insights into improvement potential in logistics theory and business operations. The insights provided serve as a starting point for future studies in this general direction, supporting human-centric, efficient, and sustainable logistics systems; the presented case acts as pars pro toto analysis, inspiring future insights in this relevant field.

CRediT authorship contribution statement

Jonas Koreis: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Matthias Klumpp:** Writing – review & editing.

Data availability

The data that has been used is confidential.

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