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The impact of working with an automated guided vehicle on boredom and performance: an experimental study in a warehouse environment

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ABSTRACT

Implementing collaborative robots in warehouse operations requires employees to engage in order picking alongside robots, which raises concerns about employees' perception of being 'robotised'. This study explores the interplay between workload and autonomy in the context of Automated Guided Vehicle (AGV)-assisted order picking, aiming to understand their joint impact on employees' boredom and performance. In a unique controlled laboratory experiment conducted within an experimental warehouse environment, 352 order pickers interacted with an actual AGV to retrieve items from various aisles and deliver them to a depot station. Using a 2 × 2 between subject design, participants were assigned to either pick 77 products (low workload) or 231 products (high workload), and to walk behind the AGV (low autonomy) or walk in front of the AGV (high autonomy). Participants in the high-workload low-autonomy condition were less bored but performed poorer than those in the low-workload low-autonomy condition. No significant differences in boredom and performance between the low-workload high-autonomy condition and the high-workload high-autonomy condition were found. Our findings emphasise the importance of considering the effects on employees when implementing AGV-assisted order picking. To alleviate boredom among order pickers due to such tasks, it is important to provide autonomy while carefully managing workload levels to maintain optimal performance.

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Introduction

With the explosive growth in logistics transport demand, improving the efficiency of logistics warehouses has become a critical challenge. As a result, the massive deployment of robots such as Automated Guided Vehicles (AGVs) in warehouses has emerged as a significant trend in the logistics industry. Recently, many platforms, such as Amazon, JD.com, and Cainiao, have increasingly adopted AGVs to provide warehouse services, enhancing work efficiency and reducing transport costs (Li and Huang 2024). Implementing such robots has revolutionised the logistics warehousing industry, specifically the order picking process (Vijayakumar and Sobhani 2023). This process comprises retrieving products from storage locations to fulfil specific customer orders in several steps, ranging from clustering customer orders to disposing of the picked products (de Koster, Le-Duc, and Roodbergen 2007). This widespread adoption underscores the relevance of studying the effects of AGVs on human workers, particularly in terms of autonomy and workload. While AGVs are designed to improve the performance of order pickers and reduce errors (Dhaliwal 2020; Jacob et al. 2023), they may also lead to a sense of being 'robotised' among employees, potentially reducing their perceived autonomy (Berkers, Rispens, and Le Blanc 2023; Loske 2022). Additionally, employees may encounter an increase in their workload when working alongside robots (Gutelius and Theodore 2019).

The introduction of robots in warehouses may alter the nature of human work (Boysen and de Koster 2024), often shifting the role of order pickers from active engagement to more passive supervision of robotic tasks (Hosseini et al. 2024). This shift can heighten the risk of boredom and impact performance. As Boysen and de Koster (2024) note, integrating human factors, such as performance-related behaviours, into operational research models has become a top priority in warehousing research, given the strong influence of human factors on individual picking performance. Order pickers' roles inherently involve performing monotonous repetitive

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tasks (Vanheusden et al. 2023). The increased presence of robots in the workplace, which renders numerous tasks tedious and unstimulating, may further contribute to pickers' proneness to boredom (Cimini et al. 2020; Cragg and Loske 2019; Cummings, Gao, and Thornburg 2016) and impact their performance (De Lombaert et al. 2023; Koreis, Loske, and Klumpp 2023). Previous cross-sectional studies have either investigated autonomy *or* workload and their relationship with employee boredom and performance and yielded mixed results. For example, in a survey among employees from various departments (e.g. Finance, HR) at the national head office of a large company, van Hooff and van Hooft (2017) found that a lack of autonomy was related to boredom. Moreover, Reijseger et al. (2013) suggest that unchallenging roles increase the likelihood of boredom, which, according to van Wyk et al. (2016), is associated with reduced job satisfaction and organisational commitment.

Furthermore, two other laboratory studies investigated the effects of work pace (comparable to workload) on performance. Bosch et al. (2011) found that although participants working at a higher pace were more productive, they did make more mistakes in assembly tasks. Roy and Edan (2020) focused on handover tasks in supermarkets and found that participants working at a high pace were not necessarily more productive than those working at a normal pace. Next to studies that are not related to working with (collaborative) robots, experimental research conducted by Pasparakis, De Vries, and De Koster (2021) investigated whether the manipulation of order pickers leading and the robot following (i.e. high autonomy) and vice versa (i.e. low autonomy) affects order pickers' performance, such as productivity and accuracy in AGV-assisted order picking scenarios. They found that, although order pickers were more productive when leading the AGV, they were more accurate when following the AGV. Thus, the *joint* impact of workload and autonomy on employee boredom and performance in a robotised environment is still unclear.

This study draws upon Job Demands-Resources (JD-R) theory (Bakker, Demerouti, and Sanz-Vergel 2023) and seeks to extend JD-R literature. The JD-R theory posits that the job demands (e.g. workload) and job resources (e.g. autonomy) of a job jointly predict outcomes of boredom and performance. We aim to contribute two-fold to the growing literature on how robotisation impacts warehouse employees' boredom and performance. First, although numerous longitudinal studies (Lesener, Gusy, and Wolter 2019) explored the relationships between various job demands, job resources, and work-related outcomes within the context of this theory, it is essential to note that longitudinal relations do not necessarily establish causation because of the potential influence of third variables or confounders (Bakker and Demerouti 2017). To establish cause-and-effect relationships, Bakker and Demerouti (2017) and Stoner, Felix, and Stadler Blank (2023) highly recommend experimentally manipulating job characteristics to investigate whether these manipulations produce the expected effects. The second contribution we make is building upon the experimental study of Pasparakis, De Vries, and De Koster (2021) by taking over their autonomy manipulation and introducing an additional element: the manipulation of workload. Given that (collaborative) robots might increase order pickers' workload, such as by pressuring employees to pick more orders within the same timeframe, adding this element allows us to explore how autonomy and workload *jointly* influence boredom and performance in AGV-assisted order picking. Experimental research on the *joint* effects of autonomy and workload in realistic (work) settings where humans collaborate with robots is extremely scarce but highly relevant as it resembles the real work environment which contains the simultaneous impact of various job characteristics. Third, while most experimental studies typically involve first-year university students, particularly in psychology, we involve 352 logistics Vocational Education and Training (VET) students. This high number of participants significantly strengthens our study, particularly when compared to other experimental studies, which often include sample sizes of only 27 to 60 students (e.g. De Lombaert et al. 2024a; Pasparakis, De Vries, and De Koster 2021, 2023). These students have either worked as order pickers or will do so in the future, representing the next generation of logistics employees (De Lombaert et al. 2024b; de Vries, de Koster, and Stam 2016).

Theory and hypothesis development

Job demands-resources theory

Our research model is presented in Figure 1(A,B). To explain how job demands (e.g. workload) and job resources (e.g. autonomy) jointly predict outcomes of boredom and performance, we use the Job Demands-Resource (JD-R) theory (Bakker, Demerouti, and Sanz-Vergel 2023) a state-of-the-art theory from organisational psychology. The JD-R theory posits that all job characteristics can be classified into two broad categories: job demands and job resources. Job demands refer to physical, emotional, or cognitive efforts required by the job, which can be either challenging or hindering. Job resources, on the other hand, are aspects of the job that help employees achieve their goals, reduce job demands, and stimulate personal growth and development.

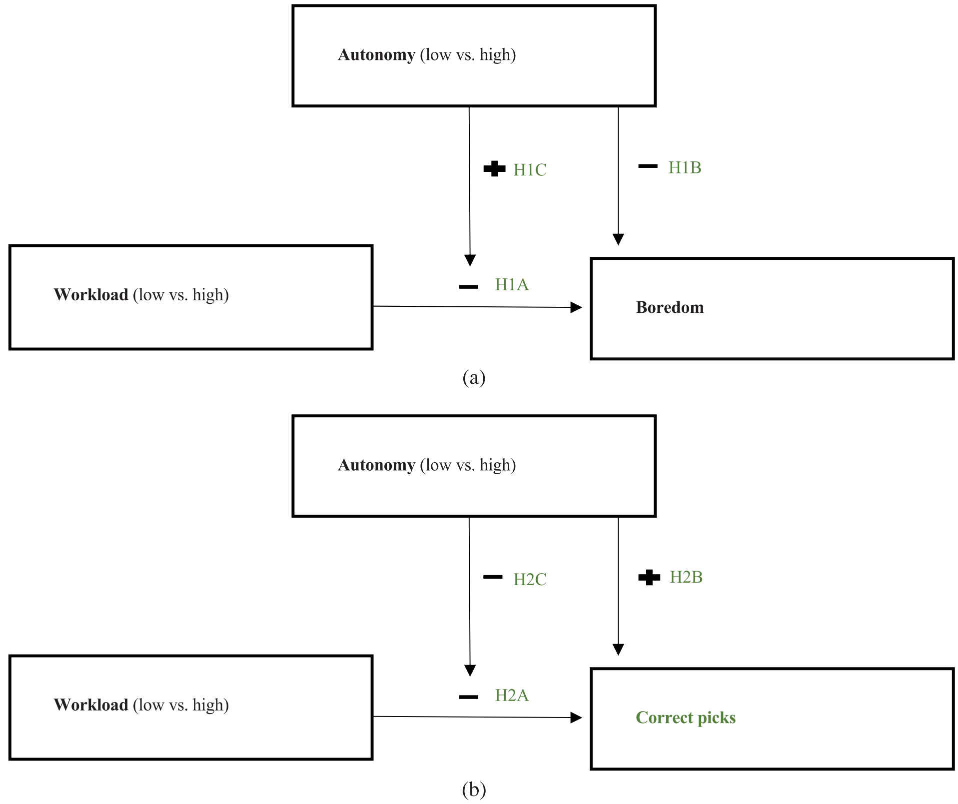

Figure 1. (A and B) Conceptual model.

Within this framework, job resources like autonomy are particularly relevant in human-robot collaboration settings, as they can enhance performance by motivating employees through growth and goal achievement. In contrast, job demands such as workload may lead to strain, particularly in high-paced, high-pressure environments like warehouses (Demerouti and Bakker 2023). The Job Demand-Control (JDC) model (Karasek and Theorell 1990) is important here, as it was among the first to explore how job demands (e.g. workload) and job control (e.g. autonomy) interact to influence employee stress and well-being. Its pioneering idea – that job control can mitigate the negative effects of high job demands, thereby reducing stress-related outcomes like burnout – remains relevant.

However, unlike the JDC model, the JD-R theory offers a broader framework that builds on this foundation, making it especially pertinent in the complex, evolving settings of modern workplaces, such as those integrating robotics. The JD-R theory introduces two integrated processes – the health-impairment process and the motivational process – allowing for a more nuanced understanding of how the work context in logistics influences a broad set of outcomes, including performance and boredom. The JD-R model's flexibility is particularly valuable because it recognises that multiple resources, beyond just control, can help employees manage job demands effectively. The theory shows that job demands or resources in isolation do not simply determine outcomes; rather, these outcomes, such as performance and psychological states like boredom, could emerge from the interaction between demands and resources. By broadening the scope of outcomes with JD-R, we gain deeper insights into the complex dynamics within the workplace, providing a more comprehensive view of how these factors influence employee experience and performance.

The main and interaction effects of workload and autonomy on boredom

The global warehouse robotics market, including collaborative robots (cobots), was valued at $7,069.1 million in 2023 and is projected to reach $31,343.7 million by 2032 (Dhananjay Jagtap and Mutreja 2024). As the adoption of robotic solutions in warehouse operations is expected to exceed four million robots installed across 50,000 warehouses worldwide by 2025, it becomes crucial to understand how these technologies impact human workers (Jacob et al. 2023). Despite the growing presence of robotics in logistics warehouses, human operators still need to collaborate with them (Lorson, Fügener, and Hübner 2023; Pasparakis, De Vries, and

De Koster 2023; Winkelhaus, Grosse, and Glock 2022). Warehouse robots are not only implemented to improve ergonomics and reduce repetitive tasks for employees (Koreis, Loske, and Klumpp 2023), but they are also used to speed up processes and increase the number of completed assignments (Bolu and Korcak 2021), which impacts job demands. As robots allow for the continuous monitoring of order pickers' activities, including task execution, time allocation, and speed, order pickers could feel compelled to match the pace set by the robots to meet the pick targets (Berkers, Rispens, and Le Blanc 2023). So their workload could be intensified, i.e. they have to do more work within a specific time (van Veldhoven et al. 2015). Thus, collaborative tasks between order pickers and robots could be categorised as intensive and high-paced work.

The introduction of AGVs has transformed traditional warehouse tasks, potentially altering the nature of autonomy experienced by employees (Thylén, Wänström, and Hanson 2023), which is a job resource. Autonomy refers to employees' discretion on when, where, and how to carry out tasks, including the sequence and method of completion (Zhou 2020). AGVs are able to perform order picking tasks in collaboration with humans by following predetermined paths to autonomously navigate through the warehouse and aid human pickers by carrying the crates for collected orders (Löffler, Boysen, and Schneider 2022). This type of collaboration might reduce human pickers' autonomy in deciding when and where to execute their picking tasks (Smids, Nyholm, and Berkers 2020). However, when collaborating with AGVs, human pickers are still the ones responsible for finding the correct orders from shelves, and picking and placing them in the crates (Lee, Chang, and Karwowski 2020). In fact, most AGVs do not (yet) automatically replan their route in case of unexpected obstacles along the way (Löffler, Boysen, and Schneider 2022), which means that human pickers are needed to guide them to the correct picking area when such obstacles are encountered. Consequently, human pickers still have some autonomy left in how they carry out their tasks and in what order.

In line with the motivational process, we expect that workload acts as a challenge job demand (Harju, Van Hootegem, and De Witte 2022) and autonomy as a job resource, and both may reduce boredom. Boredom is defined as a subjective experience marked by a sense of dissatisfaction and low arousal due to a lack of challenges and meaning in the workplace (Schaufeli and Salanova 2014; Striler and Jex 2023). Since the risk of understimulation in picker jobs is high (Lager, Virgillito, and Buchberger 2021), order pickers need to experience a certain level of job demands to feel stimulated. Van den Broeck et al. (2010) pointed out that an abundance of demands, such as a high workload, could be considered a source of challenge and stimulation, requiring employees to focus on their tasks. In fact, in their survey study among Swiss white- and blue-collar employees across various professional domains, Toscanelli et al. (2022) found that job demands, for example workload and time pressure, were negatively related to boredom. Therefore, it could be inferred that having to pick orders quicker because of an increased amount of work might diminish boredom.

Moreover, in line with the JD-R theory, we expect autonomy as a job resource to be a stimulating job aspect that enhances employee work engagement (i.e. thus reduces boredom). Work engagement can be defined as a positive, fulfilling, work-related state of mind characterised by vigour, dedication, and absorption (Schaufeli et al. 2002). It often stands in contrast to feelings of boredom, as engaged employees are typically more enthusiastic and absorbed in their work tasks. Several studies in different professions and sectors have shown that those who experience a low level of autonomy could be more prone to boredom (Alvarez et al. 2009; Pekrun et al. 2010; Schwartze et al. 2021; van Hooff and van Hooft 2017), meaning that high level of autonomy may reduce employees' boredom. For example, an experimental study among undergraduates found that those who believed they had more control experienced less boredom (Struk, Scholer, and Danckert 2021). While the context of students in an experimental setting may differ from that of warehouse employees, these findings provide a useful basis for hypothesising that similar mechanisms may operate in workplace settings. Specifically, it suggests that employees might experience less boredom when they perceive a high level of autonomy in their job.

Furthermore, the JD-R theory posits that any job resource, including autonomy, may alter the effects of job demands (e.g. workload) on work-related outcomes (Bakker, Demerouti, and Sanz-Vergel 2023). The underlying rationale is that increased autonomy enables employees to respond to high job demands when and how they are most capable of doing so. For example, consider order pickers in a warehouse setting: if they have high autonomy, they can decide the sequence and pace of picking tasks, potentially managing their workload more effectively and reducing feelings of monotony. This flexibility can mitigate the negative impact of a high workload, making the job less boring.

In contrast, pickers with low autonomy, who must follow a strict schedule and order of tasks dictated by the system, might feel overwhelmed or bored when faced with the same high workload, as they have fewer opportunities to adjust their work process. This scenario aligns with a systematic review by Tummers and Bakker

(2021), which found that individuals with high autonomy are generally better equipped to handle high workloads. Building on the JD-R theory and its application to human-robot collaboration in warehouses, we, therefore, expect that autonomy will moderate the negative effect of workload on boredom and formulate the following hypotheses:

> Hypothesis 1A–C: Workload (1A) and autonomy (1B) are negatively related to boredom. The negative effect of workload on boredom is moderated by autonomy, such that it is stronger when autonomy is high than when autonomy is low (1C).

The main and interaction effects of workload and autonomy on performance

Although warehouses deploy (collaborative) robots to improve ergonomics and reduce repetitive tasks for employees, thereby enhancing the overall work environment, they also aim to boost human performance in the order picking process, as high performance could form the core of their business (Jaghbeer, Hanson, and Johansson 2020). In fact, Lucchese, Panagou, and Sgarbossa (2024) found in their experimental study that participants perceived higher performance using a pick-by-light technology, which sped up identifying and selecting items from the shelves. In collaborative order picking, a picker is paired with a robot. They move together to the designated pick location, where the robot provides instructions on what, where and how many products to pick. The person then executes the tasks, placing the required products in the crates. Employee performance can be defined as achieving work goals or completing tasks that have been given to them on time (Putra and Ali 2022). In other words, it is the level of achievement of results for carrying out the most essential task in one's job on time (Susanto, Syailendra, and Suryawan 2023). A systematic literature review by Chondromatidis, Gialos, and Zeimpekis (2022) points out that accuracy, i.e. the number of correctly picked products, is one of the most important performance measurement indicators in the order picking process, which is also the one we focus on in the current study (i.e. correct picks). Being accurate in order picking may result from effective collaboration between the picker and the robot, which could be influenced by the pace set by the robot (Dzieza 2020; Neumann et al. 2021).

In line with the JD-R theory, high job demands might lead to poor performance due to increasing stress and cognitive overload (Loske et al. 2024; Mihelič, Zupan, and Merkuž 2024). While individual work pace can vary, Bruggen (2015) and Mauno et al. (2023) found that a higher workload is linked to reduced job performance, considering workload as a barrier and a potential distraction for employees. Therefore, we expect that in a setup with a high workload pickers' performance will be worse compared to a setup with a low workload. In scenarios where the robot instructs pickers to pick a relatively high volume of products (high workload), they may indeed pick more products (i.e. higher performance quantity), but they might pick fewer correct products (i.e. lower performance quality). These directives from robots may create a form of external pressure that may override workers' intrinsic work pace. This phenomenon can occur because workers may feel compelled to meet the externally set targets and/or due to perceived time pressure, which can lead to rushed decisions and errors. On the other hand, in scenarios where the robot instructs pickers to handle a manageable volume of products (low workload), their performance will be more accurate, potentially resulting in picking more correct products.

Moreover, in line with the JD-R theory, job resources such as autonomy could lead to better performance, as employees possess an essential job resource that is needed to create a sense of control over their tasks and, therefore, are motivated and focused to perform well (Bakker and Demerouti 2017). In scenarios where pickers are leading and the robot is following, they have more autonomy over their tasks. For example, they have the autonomy to decide when and how to execute the pick, allowing them the flexibility to take their time, carefully process the order picking information, inspect and select the correct product, and double-check its accuracy before proceeding to the next location. In contrast, in scenarios where the robot is leading and the pickers are following, they can start processing the picking information and search for the required products only after the robot stops at the indicated pick position. Suppose it takes them a long time to process and find the required products. In that case, the robot might have already initiated the move to the next order picking cycle before the pickers have executed the pick or completed their double-checking process. This difference in high and low autonomy could impact performance. De Lombaert et al. (2024a) found that implementing participatory order assignments (POA) (i.e. more autonomy) in warehousing did not negatively impact productivity. In fact, 11 out of 17 interviewees expressed strong belief that introducing a POA system would enhance their performance. Consequently, we expect that in scenarios with pickers leading the robot (high autonomy) their performance will be more accurate, potentially resulting in picking more correct products than in scenarios with pickers following the robot (low autonomy). Therefore, we argue that autonomy is positively related to order pickers' performance. However, some studies suggest that autonomy may not always positively impact productivity. For example, Pasparakis, De Vries, and De Koster (2021) found that human-following setups (lower autonomy) were superior in terms of accuracy (−0.66 errors per 20 min), while human-leading setups (higher autonomy) resulted in greater order-picking productivity (+8.3% average productivity advantage). Nevertheless, in line with the theory and other studies, we expect that autonomy will positively affect performance, in terms of quality, in our experimental context.

Furthermore, in line with the buffering hypothesis, we expect that autonomy in determining how one carries out tasks could help employees achieve better performance, suggesting that autonomy could buffer the negative impact of workload on performance. While not extensively studied in the warehousing context, in a study among 878 Israeli social workers, Axelrad-Levy et al. (2023) found that job autonomy significantly buffered the adverse effects of perceived workload on perceived job performance. Building on the JD-R theory and its application to human-robot collaboration in warehouses, we, therefore expect that autonomy will weaken the negative effect of workload on order pickers' performance and formulate the following three hypotheses:

> Hypothesis 2A–C: While workload is negatively related to correct picks (2A), autonomy is positively related to correct picks (2B). Autonomy buffers the negative relationship between workload and correct picks, such that the effect of workload on correct picks is weaker in the high autonomy conditions vs. low autonomy conditions (2C).

Methodology

Participants

The hypotheses were tested using data obtained from a laboratory experiment with 352 participants over four months from September 2022 to December 2022. Prior to the main experiment, we conducted a pilot study in June 2022 with 40 participants, ten per condition, to assess whether the experimental conditions were working as intended and evaluated the comprehensibility of all the questions we asked, including the written instructions in Table A1 in Appendix 2. In the pilot, we asked participants in each condition whether they understood the questions and instructions, ensuring the language was clear and appropriate. We also consulted a teacher to review the questions, making revisions to any ambiguous wording based on their feedback. Participants were randomly allocated to four experimental conditions, each comprising 88 participants. The participants were students from a school for vocational education in shipping and transport in the Netherlands who were trained to become logistics employees. Participants were involved in the experiment individually and received course credits as compensation. Each student participated entirely voluntarily on their own, and the credits awarded were for their individual performance in the study, not influenced by the actions of other participants. There were 135 students at study level 3 (38.4%) and 217 students at study level 4 (61.6%), representing the highest levels of VET in The Netherlands (Nuffic 2023). Among them were 214 first-year students (60.8%), 64 s-year students (18.2%), 63 third-year students (17.9%), and 11 fourth-year students (3.1%). The mean age of the participants was 18.37 years ($SD = 2.46$), and 11.4% were female, which was representative of the school's student population. Most participants did not have any previous experience in order picking (either through internship or classes) ($N = 190$; 54%), others had a bit of experience ($N = 63$; 17.9%), somewhat experience ($N = 68$; 19.3%) and a lot of experience ($N = 31$; 8.8%). Most of them also had no previous experience working with an AGV ($N = 328$; 93.2%), others had a bit of experience ($N = 20$; 5.7%), and some experience ($N = 4$; 1.1%).

Procedure

The experiment occurred in an experimental warehouse setup (Figure 2) within a 105-square-metre room measuring 14 × 7.5 metres. It featured sturdy metal racks arranged in a layout encompassing four aisles: A, B, C, and D. Specifically, aisle A and aisle D each consisted of nine sections, while aisle B and aisle C each consisted of eighteen sections, resulting in a total of 54 sections. Each section was divided into 3 levels with varying heights, resulting in a total of 162 storage locations across all aisles. Each location was clearly labelled, sequentially indicating the aisle, section, and level. For instance, a pick location identified as A.03.02 would be in aisle A, the third section, and the second level. Each pick location stored a distinct household or office product, with items ranging from small, lightweight objects like pens or dish brushes to larger items such as packs of printer paper or rolls of trash bags, weighing between 10 and 2000 grams. The product assortment spanned various categories, including cleaning supplies, stationery, greeting cards, balloons, and milk bottles, reflecting a high degree of diversity in both size and function, from everyday consumables to more specialised office items. Sufficient stock was maintained at each location to ensure uninterrupted picking during each picking session, eliminating the need for intermediate restocking.

The participants were given instructions to complete a simplified order picking task, which can be summarised in four steps: 1. Locate the requested products on the

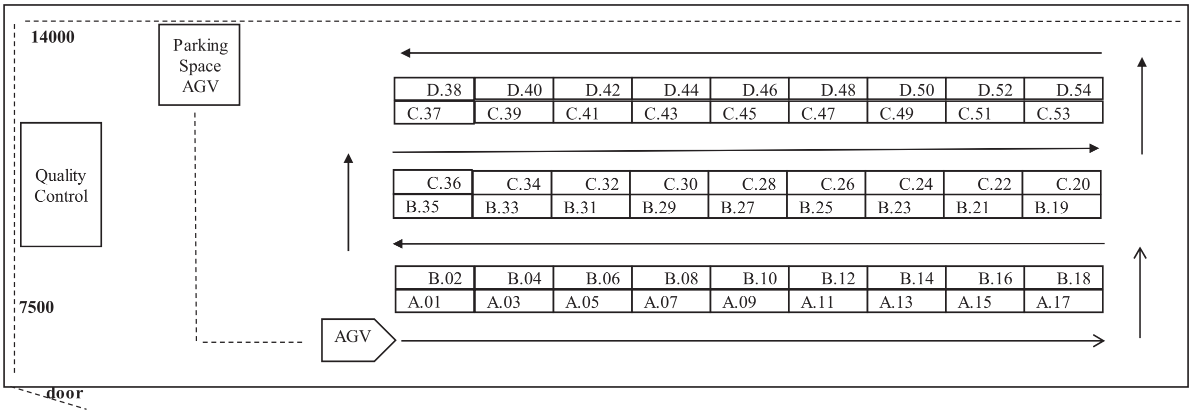

Figure 2. Warehouse layout (in mm).

(a) (b) (c)

Figure 3. (A) AGV leading the participant. (B and C) The participant leading the AGV.

order list. 2. Pick the appropriate quantity of products and put them in the order crates. 3. Confirm the pick. 4. Repeat the process when an order is complete at the next pick location. The orders were presented to the participants sequentially through a user-friendly interface on a tablet (see Figure 3(A)) or smartphone (see Figure 3(B,C)). These orders were virtually unlimited in quantity, ensuring that all participants remained occupied throughout the picking sessions. The interface furnished essential information, including the pick location, product name, and the quantity of products requested for each order. The participants were instructed to confirm each order by clicking the '*confirm order*' button when the order was completed. We created a continuous S-shaped movement to prevent them from taking shortcuts. They were forced to visit all four aisles to pick orders. Starting in aisle A (left-hand side with odd numbers), aisle B (left-hand side even numbers, right-hand side odd numbers), aisle C (right-hand side even numbers, left-hand side odd numbers) and finishing in aisle D (left-hand side with even numbers), requiring the same total travel distance to fulfil each order. All the orders had been preselected in advance, and each order ranged from one to ten items, each requesting a distinct product.

Manipulations

In this experiment, we manipulated participants' autonomy by instructing them to walk either behind the AGV (representing low autonomy; conditions A and C) or in front of the AGV (representing high autonomy; conditions B and D). This approach was similar to the manipulation of Pasparakis, De Vries, and De Koster (2021). Additionally, we manipulated workload by assigning participants to pick 77 products (representing low workload; conditions A and B) or 231 products (representing high workload; conditions C and D). We chose these specific quantities to ensure a substantial difference between low and high workload conditions. By adding 154 products to the high workload conditions, we aimed to create a significant contrast, ensuring that participants in the high workload conditions indeed experienced a considerably higher workload. To facilitate the experimental manipulations, we employed an AGV capable of self-localisation with an accuracy of approximately $\pm$ 20 mm, utilising a 270-degree laser scanner. This AGV possessed ample cargo capacity to transport two order crates.

In conditions A and C, we equipped the rear of the AGV with a tablet mount containing real-time order information. The AGV operated autonomously in these conditions, while the participants were there to support it by following its movements and placing products into the designated crates. During these specific conditions, the AGV automatically navigated to the next pick location, with participants trailing behind. Once the AGV reached its destination, participants initiated the order picking process.

In conditions B and D, participants were equipped with smartphones fastened to their non-dominant arms, which provided access to both the current and upcoming order information and the pick locations. This setup allowed participants flexibility in either reviewing the details of the next order while still at the current pick location, deferring this information until they reached the subsequent pick location, or at any other point in between, as they saw fit. They were explicitly informed that they retained control over the process, with the AGV's role being one of support, primarily in carrying the order crates, and driving behind them.

To minimise perceived differences between conditions and ensure that any variations in picking performance were solely attributable to the experimental conditions rather than fluctuations in the AGV's performance, we implemented a Wizard of Oz method, similar to Pasparakis, De Vries, and De Koster (2021). We conveyed to the participants that the AGV could locate products within the warehouse independently or autonomously by following their movements. In reality, the AGV's actions for each set of orders were preplanned and executed at a consistent speed across all conditions when moving between identical locations. A mandatory offset was the only deviation from this consistency, accommodating the participants' positions in front of or behind the AGV. This offset ensured that participants were consistently positioned at the section's midpoint where the requested product was stored. Consequently, they halted at the same physical location (i.e. the stopping point) when picking the same product across different conditions. This approach aimed to establish comparability and control in the experiment while concealing the true nature of the AGV's operation.

Naturally, two sections on opposite sides of the same aisle, specifically B and C, shared a common stopping point (e.g. B.10 and B.27), whereas aisles A and D had distinct stopping points. The sequence of commands directing the AGV's movements was preprogrammed into its memory, and the commands to proceed to the next location were triggered each time a participant tapped the screen to confirm the previous pick.

When the AGV led the way with the participants following (i.e. low autonomy), the pickers' movements did not influence the AGV's path. Conversely, when participants were walking ahead of the AGV (i.e. high autonomy), the AGV adhered to its predefined route without overtaking the pickers, coming to a halt at a safe distance behind them, creating the illusion that it possessed no autonomy in movement. This design ensured that participants were unable to notice any operational differences, and we did not observe any indications that participants had noticed such distinctions.

Across all four conditions, participants commenced their tasks at location A.01 and concluded at D.38, following a predetermined S-shaped route. Once participants finished picking the orders, the AGV autonomously transported the crates to the quality control station (see Figure 2). Since the AGV's movement and speed remained consistent across all conditions and for all participants, any variations observed in the outcomes were solely attributable to differences in the four experimental conditions. See Appendix 2 for the phases of the experiment.

Survey measures and objective performance outcomes

All survey measures were scored on a five-point Likert scale answering format ranging from 1 (*strongly disagree*) to 5 (*strongly agree)*. While the pre-survey, consisting of demographic questions, was filled in as soon as the participants entered the lab, the following survey measures were filled in as soon as the participants finished the AGV-assisted order picking tasks. See Appendix 1 for the survey questions.

Autonomy was assessed with five slightly reformulated items from the Work Design Questionnaire by Morgeson and Humphrey (2006). For example, 'When I think back to order picking, I was in charge of the AGV'. Cronbach's α was .85.

Workload was assessed with five slightly reformulated items from the Questionnaire for the Experience and Evaluation of Work by van Veldhoven et al. (2015) that refer to pace and amount of work. For example, 'When I think back to order picking, I had to pick too many orders'. Cronbach's α was .89.

Boredom was assessed with five slightly reformulated items from the Dutch Boredom Scale (DUBS) by Reijseger et al. (2013). For example, 'When I think back to order picking, I was bored during order picking'. Cronbach's α was .83.

Correct picks as an indicator of performance was objectively measured during the actual picking round, and we assessed whether participants accurately picked both the required product and required quantity. If participants

Table 1. Means, standard deviations, and correlations between key variables.

	Mean	SD	1	2	3	4	5	6
1. Autonomy: low (0) and high (1)	.50	.50	–					
2. Workload: low (0) and high (1)	.50	.50	.00	–				
3. Autonomy (1–5)	3.22	1.14	.85***	–.06	–			
4. Workload (1–5)	2.20	.92	–.37***	.43***	–.49***	–		
5. Boredom (1–5)	2.12	.79	–.30***	–.12*	–.37***	.07	–	
6. Correct picks (1–100%)	89.60	9.46	.34***	–.29***	.28***	–.40***	–.08	–

Notes: $N = 352$ participants; a robustness check was conducted by including sociodemographic variables (i.e. age, sex and education level) in the correlations analysis. The significance of the key variables remained unchanged, indicating that the results are robust to their inclusion. Consequently, the sociodemographic variables were excluded.
*$p < .05$.
***$p < .001$.

successfully picked the correct product and quantity as instructed, it was recorded as a correct pick (coded as the quantity of the product). However, any deviation from the required product or quantity resulted in an incorrect pick (coded as 0). For example, if participants were instructed to pick three black pens and they picked exactly three black pens, it was considered as three correct picks (coded as 3). Conversely, if they picked any other product or an incorrect quantity, it was considered as an incorrect pick (coded as 0). We calculated the percentage of correct picks for each participant at every location and averaged the results across all locations.

Results

We used one-way ANOVA to statistically confirm that the intended conditions were effectively established. We also checked for normality and homogeneity of variances prior to the analysis. Although these assumptions were not fully met, ANOVA remains appropriate due to its robustness in large samples; for full details, see Appendices 3 and 4.

Table 1 displays means, standard deviations, and correlations among the studied variables.

The main and interaction effects of workload and autonomy on boredom

Hypotheses 1A and 1B proposed that workload and autonomy are negatively related to boredom. Performing a two-way multivariate analysis of variance (two-way MANOVA) using SPSS (version 27), we found that both the main effect of condition workload, $F(1, 348) = 5.61$, $p = .02$, partial $\eta^2 = .02$, and the main effect of condition autonomy were significant, $F(1, 348) = 35.55$, $p < .001$, partial $\eta^2 = .09$ (see Table 2). Specifically, in line with hypotheses 1A and 1B, we found that participants in the high workload condition, $M = 2.03$, 95% CI [1.92, 2.14], and in the high autonomy condition, $M = 1.89$, 95% CI [1.77, 2.00] were significantly less bored than participants in the low workload condition, $M = 2.22$, 95% CI [2.11, 2.33], and in the low autonomy condition, $M = 2.36$, 95% CI [2.25, 2.47] (see Table 3), respectively. Hypothesis 1C proposed that the negative effect of workload on boredom is moderated by autonomy, such that this relationship is stronger when autonomy is high than when autonomy is low. The workload × autonomy interaction was significant, $F(1, 348) = 5.74$, $p = .02$ partial $\eta^2 = .02$ (see Table 2). As shown in Figure 4, workload only negatively effects boredom when autonomy is low. When autonomy is high, workload has no impact on boredom, therefore rejecting hypothesis 1C. Subsequent simple effects analyses showed that boredom was significantly lower in the high-workload low-autonomy condition, $M = 2.17$, 95% CI [2.01, 2.33], compared to the low-workload low-autonomy condition, $M = 2.55$, $F(1, 348) = 11.35$, $p < .001$. Conversely, the low-workload high-autonomy condition, $M = 1.88$, 95% CI [1.73, 2.04], and the high-workload high-autonomy condition, $M = 1.89$, 95% CI [1.73, 2.04], did not differ significantly, $F(1, 348) = .00$, $p = .98$ (see Tables 4 and 5).

The main and interaction effects of workload and autonomy on performance

Hypothesis 2A proposed that workload is negatively related to correct picks, and hypothesis 2B proposed that autonomy is positively related to correct picks. Performing a two-way MANOVA, we found that both the main effect of condition workload, $F(1, 348) = 38.29$, $p < .001$, partial $\eta^2 = .10$, and the main effect of condition autonomy were significant, $F(1, 348) = 53.05$, $p < .001$, partial $\eta^2 = .13$ (see Table 2). Specifically, in line with hypotheses 2A and 2B, we found that participants in the high workload condition, $M = 86.90$; 95% CI [85.69, 88.12] had a significantly lower percentage of correct picks than participants in the low workload condition, $M = 92.29$; 95% CI [91.09, 93.51], and that participants in the high autonomy, $M = 92.77$; 95% CI [91.56, 93.99], had a significantly higher percentage

Table 2. Main and interaction effect for condition workload (low vs. high) and autonomy (low vs. high).

		df	MS	*F*	Effect size
Workload (low vs. high)	Boredom	1	3.13	5.61*	.02
	Correct picks (%)	1	2558.08	38.29***	.10
Autonomy (low vs. high)	Boredom	1	19.85	35.55***	.09
	Correct picks (%)	1	3543.83	53.05***	.13
Condition workload (low vs. high) × Condition autonomy (low vs. high)	Boredom	1	3.21	5.74*	.02
	Correct picks (%)	1	2036.91	30.49***	.08
Error	Boredom	348	.56		
	Correct picks (%)	348	66.81		

Notes: MS = Mean squares; effect size = partial η^2. The *F* tests the effect of workload (low vs. high) and autonomy (low vs. high). This test is based on the linearly independent pairwise comparisons among the estimated marginal mean. As age, sex, education level, study year, picking experience and AGV experience of participants were not significantly related to the outcome variables, they were not controlled for in the analyses.
$^*p < .05$.
$^{***}p < .001$.

Table 3. Separate means, SE, and 95% CI for condition workload (low vs. high) and condition autonomy (low vs. high).

		Workload (low vs. high)					Autonomy (low vs. high)			
		Mean	SE	95% CI			Mean	SE	95% CI	
Boredom	Low workload	2.22	.06	2.11	2.33	Low autonomy	2.36	.06	2.25	2.47
	High workload	2.03	.06	1.92	2.14	High autonomy	1.89	.06	1.77	2.00
Correct picks (%)	Low workload	92.30	.62	91.08	93.51	Low autonomy	86.43	.62	85.22	87.64
	High workload	86.90	.62	85.69	88.12	High autonomy	92.77	.62	91.56	93.99

Note: SE = standard error; 95% CI = 95% confidence interval; each condition consists of $N = 88$ participants and total $N = 352$ participants.

Table 4. Means, SE, and 95% CI for the interaction between condition workload (low vs. high) and condition autonomy (low vs. high).

	Condition workload (low vs. high) × Condition autonomy (low vs. high)					
			Mean	SE	95% CI	
Boredom	Low workload	Low autonomy	2.55	.08	2.39	2.71
		High autonomy	1.88	.08	1.73	2.04
	High workload	Low autonomy	2.17	.08	2.01	2.33
		High autonomy	1.89	.08	1.73	2.04
Correct picks (%)	Low workload	Low autonomy	91.53	.87	89.82	93.24
		High autonomy	93.06	.87	91.35	94.78
	High workload	Low autonomy	81.33	.87	79.61	83.04
		High autonomy	92.48	.87	90.77	94.20

Note: SE = standard error; 95% CI = 95% confidence interval; each condition consists of $N = 88$ participants and total $N = 352$ participants.

Table 5. Interaction effects between condition autonomy (low vs. high) and condition workload (low vs. high).

	Condition workload (low vs. high) × Condition autonomy (low vs. high)					
			df	MS	*F*	Effect size
Boredom	Low autonomy	Contrast	1	6.34	11.35***	.03
		Error	348	.56		
	High autonomy	Contrast	1	.00	.00	.00
		Error	348	.56		
Correct picks (%)	Low autonomy	Contrast	1	4580.16	68.56***	.16
		Error	348	66.81		
	High autonomy	Contrast	1	14.83	.22	.00
		Error	348	66.81		

Notes: MS = Mean squares; effect size = partial η^2. Each *F* tests the simple effects of workload (low vs. high) within each level combination of the effects of autonomy (low vs. high). These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.
$^*p < .05$.
$^{***}p < .001$.

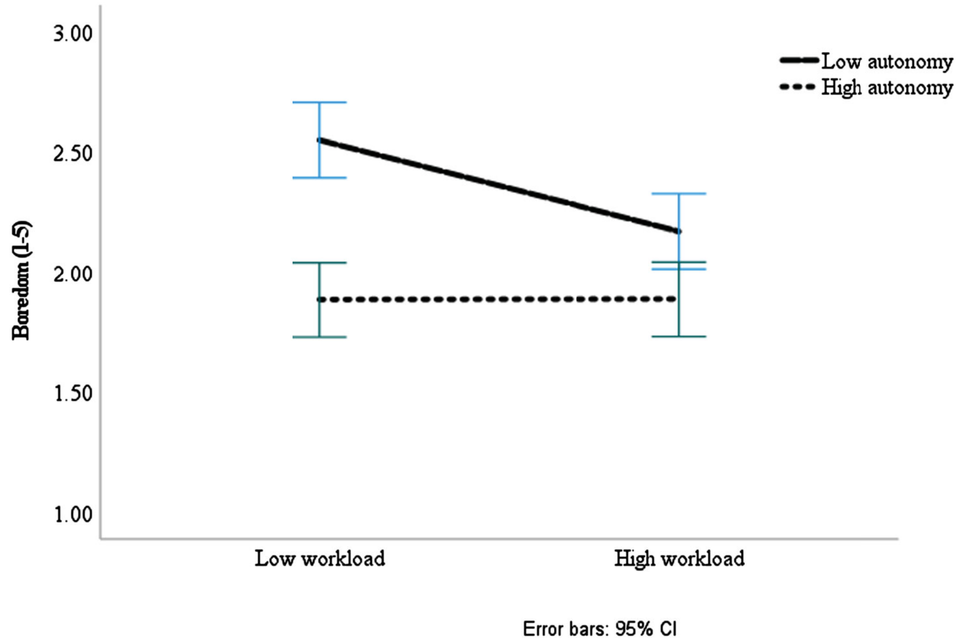

Figure 4. Interaction effects of workload and autonomy on boredom.

of correct picks than participants in the low autonomy condition, $M = 86.43$; 95% CI [85.22, 87.64], respectively (see Table 3). Hypothesis 2C proposed that autonomy would buffer the relationship between workload and correct picks, such that the effect of workload on correct picks would be weaker in the high autonomy conditions than in the low autonomy conditions. The workload × autonomy interaction was significant, $F(1, 348) = 30.50$, $p < .001$, partial $\eta^2 = .08$ (see Table 2). As displayed in Figure 5, reduced percentage of correct picks was particularly evident in the high-workload low-autonomy condition. In line with hypothesis 2C, subsequent simple effects analyses showed that the percentage of correct picks was significantly lower in the high-workload low-autonomy condition, $M = 81.33$, 95% CI [79.61, 83.04], $F(1, 348) = 68.56$, $p < .001$ compared to the low-workload low-autonomy condition, $M = 91.53$, 95% CI [89.82, 93.24]. Conversely, the low-workload high-autonomy condition, $M = 93.06$, 95% CI [91.35, 94.77], and the high-workload high-autonomy condition, $M = 92.48$, 95% CI [91.77, 94.20], did not differ significantly, $F(1, 348) = .22$, $p = .64$ (see Tables 4 and 5).

Additional analyses: types of mispicks

In addition, we delved into the types of mispicks since these could reduce throughput and efficiency. Qualitative mispicks occurred when participants picked the wrong product which was coded as 1, while correct picks were coded as 0. We only found that participants in the high autonomy condition, $M = 1.65$, 95% CI [1.33, 1.97], had a significantly lower percentages of qualitative mispicks than participants in the low autonomy condition, $M = 2.21$, 95% CI [1.89, 2.54], $F(1, 348) = 5.83$, $p < .02$. However, no significant differences were found for low vs. high workloads, and neither between the four conditions.

Quantitative mispicks occurred when participants picked the wrong quantity of correct products (more or fewer) than instructed, coded as 1, while correct quantity picks were coded as 0. We found that participants in the high workload condition, $M = 4.11$, 95% CI [3.63, 4.60], had a significantly higher percentage of quantitative mispicks than participants in the low workload condition, $M = 1.5$, 95% CI [1.10, 2.07], $F(1, 348) = 52.26$, $p < .001$. No significant differences were found for low vs. high autonomy. Across all conditions, participants in the high-workload low-autonomy condition had a significantly higher percentage of quantitative mispicks, $M = 4.91$, 95% CI [4.22, 5.59], compared to those in the low-workload low-autonomy condition, $M = 1.19$, 95% CI [.50, 1.87], $F(1, 348) = 58.86$, $p < .001$. Similarly, participants in the high-workload high-autonomy condition had a significantly higher percentage of quantitative mispicks, $M = 3.31$, 95% CI [2.63, 4.00], compared to those in the low-workload high-autonomy condition, $M = 1.99$, 95% CI [1.30, 2.68], $F(1, 348) = 7.20$, $p < .01$.

Omissions occurred when no products were picked, which were coded as 1, while picked products were coded as 0. We found that participants in the high workload

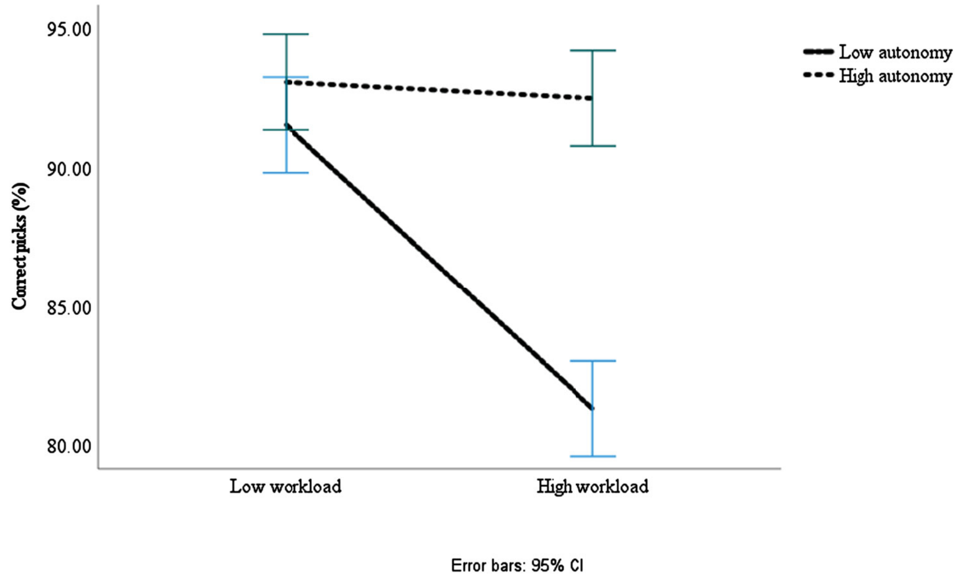

Figure 5. Interaction effects of workload and autonomy on correct picks.

condition, $M = 6.55$, 95% CI [5.79, 7.32], had a significantly higher percentage of omissions than participants in the low workload condition, $M = 2.57$, 95% CI [1.81, 3.33], $F(1,\ 348) = 52.58$, $p < .001$ and that participants in the high autonomy condition, $M = 1.39$, 95% CI [.63, 2.16], had a significantly lower percentage of omissions than participants in the low autonomy condition, $M = 7.73$, 95% CI [6.97, 8.49], $F(1,\ 348) = 133.08$, $p < .001$. Across all conditions, participants in the high-workload low-autonomy condition had a significantly higher percentage of omissions, $M = 11.92$, 95% CI [10.84, 13.00], compared to those in the low-workload low-autonomy condition, $M = 3.54$, 95% CI [2.46, 4.62], $F(1,\ 348) = 116.44$, $p < .001$. However, no significant difference was found between low-workload high-autonomy, $M = 1.60$, 95% CI [.52, 2.68], and high-workload high-autonomy conditions, $M = 1.19$, 95% CI [.10, 2.27], $F(1,\ 348) = .29$, $p = .59$.

Discussion

Building upon previous research findings within JD–R literature (Bakker, Demerouti, and Sanz-Vergel 2023), the main aim of our study was to understand the joint impact of workload and autonomy on warehouse order pickers' boredom and performance. First, we found that participants in the high workload and high autonomy conditions were less bored compared to those in the low workload and low autonomy conditions. Also, participants in the high workload and low autonomy conditions performed poorer compared to those in the low workload and high autonomy conditions. Second, we found that participants in the high-workload low-autonomy condition were less bored but performed poorer than those in the low-workload low-autonomy condition. No significant differences in boredom and performance between the low-workload high-autonomy condition and the high-workload high-autonomy condition were found.

Theoretical implications

This study significantly contributes to the existing JD-R and robotisation literature by examining how robots such as AGVs impact warehouse employees' job characteristics, as well as their boredom and performance. This investigation aims to deepen our understanding of the factors supporting or undermining these work-related outcomes. Drawing on the insights of Bakker and Sanz-Vergel (2013), who highlighted that the same job demands can be perceived as both challenging and hindering across various occupational settings, we took a novel approach by conducting our research within the context of robotisation in warehousing. Furthermore, our study enriches both knowledge areas by employing an experimental research design, which is less common compared to the more typical reliance on surveys and interviews in existing studies. This approach allows for a more controlled investigation of the effects of robotisation on employee experiences, i.e. to explore how employees subjectively experience specific job demands that are associated with robotisation in modern-day workplaces. Our study reveals that job demands can indeed be both experienced as challenging and hindering in this context, contributing to motivational processes that affect employees' boredom and performance.

Second, we established causal relationships with both outcome variables through experimental manipulation of a job demand and a job resource. While the JD-R theory implies these causal relationships through longitudinal studies, our study is one of the few to examine and demonstrate support for these effects experimentally. Specifically, we found support for the motivational process, whereby workload acts as a challenge job demand and autonomy as a job resource, both decreasing a motivational outcome like boredom. Our findings support the main premise that both challenge job demands and job resources can stimulate employees to focus on their tasks, enhancing their engagement and reducing boredom. While potentially motivational, challenge job demands can also lead to poor performance when they become excessively high. We found, in line with earlier research (Bruggen 2015; Demerouti and Bakker 2023; Setayesh et al. 2022), that participants in the high workload condition had a lower percentage correct picks than participants in the low workload condition. Also, in line with earlier research (Bakker and Demerouti 2017; Bakker, Demerouti, and Sanz-Vergel 2023; van der Lippe and Lippényi 2020), we found that participants in the high autonomy condition had a higher percentage correct picks than participants in the low autonomy condition. This finding can be attributed to the increased sense of ownership that accompanies higher levels of autonomy. When employees are given more control over their work, they tend to feel a stronger sense of responsibility and ownership over their tasks, which has been shown to reduce errors and enhance performance (Parker, Wall, and Jackson 1997; Pierce, Kostova, and Dirks 2001). This is also consistent with the results of De Lombaert et al. (2024a), who found that involving employees in operational decisions does not compromise productivity. Order pickers were less likely to deviate from normative process flows when working in a system that allowed at least some level of autonomy. However, high levels of employee autonomy due to a lack of (technological) control systems carry the risk of so-called ‘maverick picking’, in which employees consciously deviate from their normative workflows, with potential negative performance effects (Glock et al. 2017). So, the level of employee autonomy should be balanced, so that employees can be involved in operational decision making while still adhering to organisational norms.

Third, in line with the JD–R theory, this study illustrates that job resources are crucial in managing challenge and hindrance job demands effectively. Under conditions of high challenge job demands, job resources are expected to strengthen their negative effect on work-related boredom. However, our findings suggest that low rather than high autonomy moderates the negative impact of workload on boredom. When autonomy was high, workload was not significantly related to boredom. These findings are consistent with the substitution hypothesis (Demerouti and Bakker 2023; Ross and Mirowsky 2010), i.e. that autonomy substitutes workload and vice versa. When workload is low, one needs high autonomy to prevent boredom. Whereas when autonomy is low, one needs high workload to avoid boredom. Under conditions of hindrance job demands, job resources are expected to act as buffers by weakening their negative effects. In line with the buffering hypothesis, which posits autonomy as a job resource capable of weakening the impact of job demands on performance (Bakker, Demerouti, and Sanz-Vergel 2023), our findings suggest that autonomy buffers the impact of workload on correct picks. In high autonomy conditions, the negative effects of workload on performance were weaker compared to low autonomy conditions. Specifically, participants had the lowest percentage of correct picks when facing high workload and low autonomy. Conversely, the highest percentage of correct picks was found in high autonomy conditions, irrespective of the workload level. This finding supports the notion that high levels of job resources, particularly autonomy, not only ease the process of handling hindrance job demands but also enhance employees’ performance by fostering a sense of ownership. Academic literature suggests that this sense of ownership motivates employees to be more diligent and careful in their work, leading to fewer mistakes (Avey et al. 2009). Furthermore, despite the differences in study setups, our findings complement those of Pasparakis, De Vries, and De Koster (2021) by highlighting the critical role of autonomy in buffering the impact of workload on correct picks. Both studies contribute to the broader understanding of human-robot collaboration, underscoring that autonomy – regardless of the specific collaboration setup – plays a pivotal role in enhancing accuracy. Together, these findings suggest that both the structure of human-robot interactions and the level of autonomy provided to workers are crucial factors in optimising performance. Therefore, high levels of job resources, particularly autonomy, can provide the means to ease the process of handling hindrance job demands and help employees achieve better performance through an increased sense of ownership and reduced error rates.

Practical implications

Given the widespread use of AGVs in the warehousing industry, as evidenced by their adoption by major companies like Amazon, JD.com, and Cainiao, the findings of this study carry significant practical implications (Li and Huang 2024). While AGVs have indeed revolutionised the order-picking process by enhancing efficiency and reducing errors, this study and Grosse et al. (2023) reveals that their impact on human workers cannot be overlooked. Our research provides practical insights for designing AGV-assisted order picking, emphasising the importance of autonomy and a manageable workload.

First, logistics managers should prioritise providing employees with a sense of autonomy over the order picking process. One effective strategy is allowing employees to walk in front of the AGV, giving the AGV a subordinate role and enabling employees to control the AGV as well as their order picking tasks. A notable example of this approach can be seen in the practices of Locus Robotics, whose robots are designed to work alongside human pickers, allowing them to guide the robot's actions and maintain control over the picking process (Bogue 2016). This setup not only improves efficiency but also enhances employee engagement by preserving their sense of autonomy. Additionally, employees should have input into the planning and executing of their tasks, such as being informed in advance about upcoming orders and their specific locations, enabling them to prepare accordingly. Providing opportunities for employees to make decisions, such as deciding independently when to proceed to the next order picking location, could further enhance their sense of autonomy (Boucher et al. 2024). Our study demonstrates that empowering employees with autonomy can reduce boredom and enhance performance.

Second, it is also crucial to ensure that the workload associated with AGV-assisted order picking remains manageable for employees by carefully monitoring and adjusting task assignments. Research suggests that insufficient workload can contribute to workplace boredom (Harju, Seppälä, and Hakanen 2023; Khan et al. 2022), while excessive workload can negatively impact their performance (Bruggen 2015). In short, it is important to maintain an optimal workload level where employees are neither underloaded (which could result in boredom) nor overloaded (which could result in mispicks, compromising their performance). Strategies such as workload balancing, task rotation, and scheduling breaks could help employees manage underload and work overload (Dias et al. 2021; Lyubykh et al. 2022; Rinaldi et al. 2021).

Third, training employees on how to use AGVs effectively is crucial. Additionally, logistics warehouses should regularly evaluate and refine their AGVs based on employee feedback and performance metrics. This iterative process could enable continuous improvement and adaptation of AGVs to evolving needs and challenges. By prioritising employee motivation and performance, organisations can maximise the benefits of AGVs while minimising potential negative consequences.

In summary, drawing from previous studies emphasising the importance of maintaining a balance in employees' workload (Fisher, Frame, and Stevens 2023; Mou 2022) and autonomy (Methnani et al. 2021; Parker and Grote 2020), we recommend that warehouse (HR) managers pay attention to these factors to decrease boredom and optimise the performance of order pickers. Based on our detailed analysis of mispicks, we specifically advise providing order pickers with higher levels of autonomy to reduce qualitative mispicks and implement lower workload levels to reduce quantitative mispicks and omissions.

Limitations and future research

Although our findings mostly support our expectations, it is crucial to acknowledge certain limitations in interpreting the results. While we used a state-of-the-art warehouse technology, i.e. an AGV, and successfully manipulated autonomy and workload, future research could consider manipulating another aspect of workload, namely workpace, too. Warehouse technology not only increases workload but also pushes employees to increase their pace. Therefore, future studies could manipulate this aspect by adjusting the pace of robots, which we – unfortunately – were unable to do due to safety constraints. The AGV's movement was also predefined to ensure comparability across the four experimental conditions. In real-world warehouses, more advanced autonomous robots, such as AMR, use an environmental representation to find the shortest and conflict-free path. This enables them to recognise barriers and identify new, unique paths when moving from one point to another (Fragapane et al. 2021), potentially leading to movement variations. These variations may influence order pickers' behaviour in ways beyond our study's scope. Future research could replicate our study in a real-warehouse environment to gain deeper insights into the dynamic interactions between autonomous robots and human pickers. It could also explore these dynamics by incorporating scenarios with multiple participants and robots to better understand how group interactions impact the effectiveness of autonomy and workload management in this setting. This approach could also minimise the observer effect, where participants may behave differently than regular warehouse workers due to feeling observed.

Despite our efforts to ensure a diverse pool of participants, our study primarily comprised male VET students preparing for logistics roles. Although some students have actual order picking experience and are the logistics workers of the future, including students instead of experienced professionals may limit the applicability of our results to real-world logistics warehouses. Moreover, as the real-life logistics workforce includes both male and female employees, future research could aim to include more women in the sample to enhance the relevance and generalisability of our findings. Additionally, it could control for participants' personal characteristics, such as regulatory focus, as well as the time of day, both of which could influence the outcomes.

Another potential limitation pertains to the duration of our order picking tasks. The relatively short time frame, ranging from approximately nine to thirteen minutes, might have restricted participants' engagement and influenced their boredom and performance. Additionally, while our focus was on accuracy and the effects of workload and autonomy, task completion time was not directly measured. This omission could limit our understanding of how these factors impact overall job performance. Future research should address these limitations by examining longer order picking tasks in real-life warehouse settings to better understand the effects of task duration on boredom and performance. Furthermore, including task completion time as a variable would provide a more comprehensive view of how workload and autonomy influence both the speed and accuracy of performance in logistics operations.

While this study's experimental design provides robust evidence for causal relationships between job characteristics and work-related outcomes, it is important to note that the controlled conditions of experiments, while useful for establishing causality, may not fully capture the complexities and long-term dynamics present in real-world settings. In contrast, longitudinal studies could offer valuable insights into how these relationships evolve over time and in natural contexts, providing a more comprehensive understanding of their sustainability. However, longitudinal designs often face challenges in establishing causality due to the inability to manipulate variables as precisely as in experiments. Therefore, future research could aim to integrate both experimental and longitudinal approaches. This integration would validate the causal mechanisms identified in experimental studies and assess their long-term implications and generalisability, thereby offering a more nuanced and holistic understanding of work-related phenomena.

Despite these limitations, our study in a unique controlled warehouse environment involving 352 participants has significantly contributed to understanding the joint effect of workload and autonomy on order pickers' boredom and performance. Our findings underscore the critical role of autonomy in mitigating boredom and optimising performance within logistics operations. However, it is essential to recognise the concept of the 'autonomy threshold' as highlighted by Parker and Grote (2020). While autonomy is a vital strategy for improving motivation and performance, granting too much autonomy beyond a certain point could become counterproductive and may vary depending on individual preferences and capabilities. Therefore, warehouse managers should balance the degree of autonomy granted to employees, ensuring it is within a range that maximises benefits without leading to potential drawbacks.

Conclusion

With the increasing integration of technologies such as AGVs in warehouse operations, the relationship between human employees and technologies must be carefully managed. Technologies that either excessively restrict or expand employee autonomy could lead to unintended consequences, such as deviant behaviours like maverick picking (Glock et al. 2017). As technology continues to shape warehouse operations, organisations should maintain a balance that empowers employees while preserving process control. By aligning technological advancements with human capabilities and providing optimal autonomy, organisations can foster a more efficient and motivating work environment, tailored to the dynamic and evolving needs of the logistics sector.

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Disclosure statement

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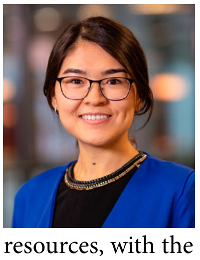
Notes on contributors



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Ethical approval

This research has received approval of Ethical Review Board (ERB) of Eindhoven University of Technology under the number ERB2022IEIS18.

Informed consent

Informed consent was obtained from all individual participants included in the study.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendices

Appendix 1. Survey questions

A.1 Pre-experimental survey

The first questions of the questionnaire are about your background information.

1. I am a:
   ○ man
   ○ woman
   ○ other
2. I am … … years old
3. I study: … … … … … … … … level … … … … … … . and I am in year … … … … … … …
4. I have experience with order picking (e.g. through an internship or practical lessons at [vocational school]).
   ○ No, I have no experience
   ○ Yes, I have a bit of experience
   ○ Yes, I have somewhat experience
   ○ Yes, I have a lot of experience
5. I have experience working with an Automated Guided Vehicle (from now on referred to as AGV).
   ○ No, I have no experience
   ○ Yes, I have a bit of experience
   ○ Yes, I have somewhat experience
   ○ Yes, I have a lot of experience

This is the end of the first questionnaire. Thank you for completing it. You can now start the experiment. A second questionnaire will follow afterwards.

A.2 Post-experimental survey

All survey measures were scored on a five-point Likert scale answering format ranging from 1 (strongly disagree), 2 (disagree), 3 (somewhat agree), 4 (agree) to 5 (strongly agree).

The following questions are about the experiment.

When I think back to the experiment …

1. I had control over order picking.
2. I was in charge of the AGV.
3. I determined the course of action during order picking.
4. The AGV had to follow me to the next pick location.
5. The AGV determined by itself when to go to the next pick location.

When I think back to the experiment …

6. I had to pick too many orders.
7. I had to work extra hard to pick all the orders.
8. I had to hurry to pick all the orders.
9. I was dealing with a backlog in order picking.
10. I had problems with the high work pace during order picking.

When I think back to the experiment …

11. I felt bored while picking orders.
12. I daydreamed while picking orders.
13. It seemed like there was no end to picking orders.
14. I tended to do other things while picking orders.
15. I had little to do while picking orders.

This is the end of the second questionnaire. Thank you for completing it.

This is the end of the experiment. [… …]

Appendix 2. Phases of the experiment

The experiment was structured into three phases. Phase 1 commenced as soon as the participant entered the warehouse. Initially, they completed a participation consent form and a demographic survey. Following this, they received an introduction and were provided with instructions by the experimenter regarding the warehouse layout. The role of the experimenter primarily involved supervising the robot, overseeing product quality and restocking after each experiment. Then, the participants were randomly assigned to one of a 2 (autonomy: low vs. high) × 2 (workload: low vs. high) between-subjects factorial experimental treatments. In phase 2, participants started with a practice round of order picking with the AGV, which lasted for five minutes. This practice round allowed them to become acquainted with the warehouse, the mechanics of order picking (e.g. routing logic, naming schemes, and electronic pick lists) and their condition. Participants were also encouraged to ask any clarification questions they had. This practice round was specifically designed to mitigate the impact of learning effects, ensuring that their performance in the actual picking round reflected genuine task engagement rather than improvements due to increased familiarity with the process. Shortly before they started the actual picking round, we handed them a piece of paper that included a short explanation of the quantity of products they needed to pick and an estimated time frame for completion. To confirm their understanding of the task, we presented them with a multiple-choice question, asking them to select the options that applied to their situation (see Table A1). Then, they commenced the actual order picking process. In Conditions A (low autonomy-low workload) and C (low autonomy-high workload), participants engaged in a twelve-minute order picking session. In contrast, in Conditions B (high autonomy-low workload) and D (high autonomy-high workload), the duration ranged from approximately nine to thirteen minutes, depending on the pace of the picker.

Phase 3 involved participants completing a post-survey to capture their psychological states and perceptions of the task

Table A1. Instructions provided to the participants in each condition *before* actual order picking.

Conditions	Instructions
Alow autonomy – low workload	The AGV determines when it moves or stops. In other words, the AGV automatically moves to the next location after 30 s. **You need to continue following the AGV.** We ask you to pick **77 products in approximately 10 min.** From experience, we know that this is easily achievable within that time frame.
Bhigh autonomy – low workload	You are free to determine when the AGV moves or stops. **In other words, the AGV follows you to the next location.** We ask you to pick **77 products in approximately 10 min**. From experience, we know that this is easily achievable within that time frame.
Clow autonomy – high workload	The AGV determines when it moves or stops. In other words, the AGV automatically moves to the next location after 30 s. **You need to continue following the AGV**. We ask you to pick **231 products in approximately 10 min**. From experience, we know that you need to work diligently to meet this deadline.
Dhigh autonomy – high workload	You are free to determine when the AGV moves or stops. **In other words, the AGV follows you to the next location.** We ask you to pick **231 products in approximately 10 min**. From experience, we know that you need to work diligently to meet this deadline.

Note*:* Answer options for all conditions were (1) I follow the AGV, (2) The AGV follows me, (3) I need to pick 77 products and/or (4) I need to pick 231 products.

Table A2. Main effects separately for condition workload (low vs. high) and autonomy (low vs. high).

	Workload (low vs. high)					Autonomy (low vs. high)			
	df	MS	*F*	Effect size		*df*	MS	*F*	Effect size
Workload	1	54.57	79.13***	.18	Autonomy	1	333.84	926.19***	.73
Error	350	.69			Error	350	.36		

Note: MS = Mean squares; effect size = partial η^2.
*$p < .05$.
***$p < .001$.

they had just performed. All forms, questions, and instructions were in Dutch. After participants finished their picking round, the experimenter checked whether they had picked the correct products and quantity.

Appendix 3. Manipulations check

While both workload and autonomy were objectively manipulated (i.e. high workload entailed picking 231 products while low workload entailed 77 products, high autonomy involved walking in front of the AGV, and low autonomy involved walking behind the AGV), we conducted univariate analyses of variance (one-way ANOVA) to statistically check the manipulation of workload and autonomy. Condition workload had a significant effect on perceived workload, $F(1, 350) = 79.13, p < .001$, partial $\eta^2 = .18$ (see Table A2). To confirm the effectiveness of the manipulation, participants in the high-workload conditions ($N = 176$) reported a significantly higher level of workload, $M = 2.60$, $SE = .06$, 95% CI [2.48, 2.71], than the participants in the low-workload conditions ($N = 176$), $M = 1.81$, $SE = .06$, 95% CI [1.69, 1.93] (see Table A3). A second one-way ANOVA showed that condition autonomy had a significant effect on perceived autonomy, $F(1, 350) = 926.19$, $p < .001$, partial $\eta^2 = .73$ (see Table A2). To confirm the effectiveness of the manipulation, participants in the high-autonomy conditions ($N = 176$) reported a significantly higher level of perceived autonomy $M = 4.20$, SE $= .05$, 95% CI [4.12, 4.28] than the participants in the low-autonomy conditions ($N = 176$), $M = 2.25$, SE $= .05$, 95% CI [2.16, 2.34] (see Table A3).

Appendix 4. Assumptions check

We conducted assumptions check for normality and homogeneity of variances prior to performing the ANOVA. However, these assumptions were not fully met. Despite this, ANOVA remains appropriate for our analysis due to the robustness of the test in large samples. Given our large sample sizes ($n = 88$ in each experimental condition, $n = 176$ in workload and autonomy, total $n = 352$), ANOVA is relatively robust to violations of normality, as the Central Limit Theorem ensures that the sampling distribution of the mean approaches normality with larger samples (Field 2013). In fact, violations of normality (even when using non-normal distributions) do not significantly compromise the results of ANOVA, particularly when other factors such as group size and group variance are controlled (Schmider et al. 2010). Additionally, with equal group sizes ($n = 88$), ANOVA is generally robust to violations of the homogeneity of variances assumption.

Table A3. Means, SE, and 95% CI separately for condition workload (low vs. high) and condition autonomy (low vs. high) separately.

	Workload (low vs. high)						Autonomy (low vs. high)				
	Mean		SE	95% CI			Mean		SE	95% CI	
Workload	Low workload	1.81	.06	1.69	1.93	Autonomy	Low autonomy	2.25	.05	2.16	2.34
	High workload	2.60	.06	2.48	2.72		High autonomy	4.20	.05	4.11	4.28

Note: SE = standard error; 95% CI = 95% confidence interval; each condition consists of $N = 88$ participants and total $N = 352$ participants.