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Assistive technologies and the human factor in warehousing: the impact of active exoskeleton on operators and picking performances

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Abstract: Warehousing plays a crucial role in modern supply chains, and picking activities, essential for warehouse operations, remain heavily reliant on human operators, often exposed to repetitive tasks and physical strain, increasing the risk of work-related musculoskeletal disorders (WMSDs). In this context, assistive technologies such as exoskeletons have emerged as promising solutions to enhance operator well-being and efficiency. This study investigates the impact of active exoskeletons on human operators and performances in parts-to-picker tasks. Using bio-signals (EMG and EEG), self-reported metrics, and productivity measures, the study evaluates impacts on human factors, i.e., on physical, cognitive, and perceived workloads, as well as on picking productivity, under varying operational conditions, finding a potential reduction of 23% of maximum muscular activity with active exoskeleton, associated to a possible reduction of productivity. The study contributes to the academic and practical understanding of assistive technologies in warehousing, offering insights into human factors and technology interplay.

Keywords: Logistics 5.0; Warehousing 5.0; exoskeleton; assistive technology; human operator's support

1. INTRODUCTION

The ongoing expansion of globalization and e-commerce is driving unprecedented growth in the logistics and warehousing sectors. From a company perspective, logistics operations are central to meeting service-level requirements, as they influence key factors such as price, product availability, delivery speed, and even sustainability. In such a challenging environment, the advent of Logistics 4.0 introduced technologies and processes that significantly improved customer satisfaction through increased customization and cost efficiency (Grosse, 2024). However, this rapid development highlights a critical bottleneck: human capital, who needs to learn how to coexist or interact with technologies. Besides, when automation and robotic solutions fail to deliver sufficient flexibility, humans frequently assume roles involving repetitive handling and management of harmful physical loads, increasing the risk of work-related musculoskeletal disorders (MSDs) and other injuries. Building on this foundation, the Warehousing 5.0 paradigm has recently emerged (Glock & Grosse, 2024). Rooted in the Industry 5.0 framework developed by the European Union (2020), this paradigm shifts the focus from purely profit-driven objectives to value-driven principles. Human-centricity, sustainability, and resilience are now recognized as essential in designing and implementing business solutions (European Commission, 2020). In this context, technology must be designed with a human-centric perspective, placing human needs and well-being at the core of operational processes. Warehousing activities, particularly picking, represent a promising area for applying these principles, given their growing complexity and impact on both customer service and operational costs, alongside the key involvement of human operators (Tudisco et al., 2024). To tackle this objective and correctly pursue human well-being, it is important to consider the human factor from different perspectives, including all its components: physical, cognitive, perceptual and psychosocial (Grosse, 2024). However, practical and academic considerations in this field usually focus on the physical aspect (Lagorio et al., 2021).

Assistive technologies, such as occupational exoskeletons, have emerged as a potential solution to these challenges. Picking, recognized as one of the most complex and physically demanding activities in warehousing, presents a critical application area for such devices (Grosse, 2024). Specifically, exoskeletons aim to reduce worker fatigue, and improve ergonomic conditions by supporting the lower spine and mitigating strain, although their impact on other aspects such as human perception of the device, freedom of movement and technology acceptance is still unclear (Ashta et al., 2023). While it is common to assess the physical impact, often using bio-signals such as electromyography (EMG), other human factors are less frequently evaluated and always through questionnaires. Perceptual (e.g., comfort) and psychosocial aspects (e.g., technology acceptance), such as device acceptance, discomfort, frustration, and usability, are typically examined more than cognitive workload. Moreover, studies on human operators mainly focus on picker-to-parts systems. While automated warehouses are becoming more common for their efficiency and space optimization, research on parts-to-picker systems often overlooks humans (Finco et al., 2023). This paper aims to address this gap by presenting an experimental case study that compares a parts-to-picker task

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assisted by an active exoskeleton with the same task performed unassisted. The study evaluates the benefits and drawbacks of each scenario, considering various contextual factors (e.g., different unit loads handled) and adopting multiple perspectives. Specifically, it examines picking performance and human well-being, considering physical, cognitive, and perceived workload. This work contributes to this research field by answering these research questions:

RQ1: How does the adoption of exoskeletons affect human factors (physical fatigue, cognitive workload, and perceived workload) and productivity performances during picking tasks in parts-to-picker systems?

RQ2: To what extent do contextual factors, such as the unit load handled, influence the effect of exoskeletons on human factors (physical fatigue, cognitive workload, and perceived workload)?

By conducting this empirical study, the paper addresses a notable gap in the growing body of literature, exploring Warehousing 5.0 solutions, which still lack substantial empirical insights.

2. RESEARCH BACKGROUND

2.1 Assistive technologies in picking: the emerging potential of exoskeletons

MSDs are among the most prevalent work-related injuries in industrialized countries, including European ones (Bevan, 2015). They contribute to disability, absenteeism, and decreased productivity. In the logistics sector, workers frequently engage in physically demanding and repetitive MMH tasks, which can lead to back overexertion (Bevan, 2015; Glock & Grosse, 2024). Various assistive technologies have been developed to enhance efficiency and support operators (Lagorio et al., 2021). Technologies like cranes and lifts, long used in warehousing, have now been joined by emerging solutions such as exoskeletons (Glock & Grosse, 2024). Exoskeletons are wearable devices that generate assistive forces/torques to enhance human strength, reduce the body’s energy consumption, and minimize damages to operators in the long term (e.g., injuries to the back caused by lifting too much weight) (Kim et al., 2019). Exoskeletons, in particular, can enhance strength and endurance, reduce musculoskeletal risks, and minimize injuries, making them a promising innovation (Glock et al., 2021). Their application in occupational tasks has gained attention only recently, with most studies focusing on passive models for manufacturing and assembly (Nussbaum et al., 2019). Research on their application in warehousing and picking is limited, yet promising, in fact, it usually reports positive results in terms of human physical fatigue reduction (Ashta et al., 2023). Exoskeletons can be designed to support specific body parts. Upper limb exoskeletons aid the arms, especially for overhead tasks, by supporting the shoulder joints. Back-support exoskeletons reduce strain on the lower back, assisting with lifting heavy loads. Lower limb exoskeletons provide support at the knees and hips (Ashta et al., 2023). Exoskeletons can also be categorized into passive and active types. Passive exoskeletons use elastic or mechanical elements to store and release energy during movement, making them simpler and more cost-effective for widespread use (Ashta et al., 2023). Conversely, active exoskeletons employ actuators controlled by sensors to enhance human strength, offering advanced capabilities but at higher costs and complexity (Ashta et al., 2023). In the logistics field, passive exoskeletons dominate both academic research and practical applications due to their simplicity and cost advantages, while the potentialities of active exoskeletons are still overlooked.

2.2 Impact of exoskeleton on the human factor

Papers studying exoskeleton applications at warehouses are limited, but they usually report a positive impact on the physical workload of operators. Conversely, impacts on cognitive, perceptual or psychosocial dimensions are less investigated and lead to different results. Schmalz et al. (2022) and Schrøder Jakobsen et al. (2023) examined the physical effects of a passive shoulder exoskeleton and a back-support exoskeleton, respectively, on human operators involved in manual material handling (MMH) in warehouses. Both studies reported a significant reduction in physical load. Similarly, Motmans et al. (2019) explored the use of a passive exoskeleton for order-picking tasks, highlighting a 9–12% decrease in erector spinae muscle activity and a reduction in perceived physical workload. However, users noted increased energy demands during downward movements against the resistance of the exoskeleton. Despite these challenges, the usability evaluation showed high acceptance among workers, with only minor criticisms regarding certain movements. Further research (Kinne et al., 2020) also demonstrated the benefits of passive back-support exoskeletons in reducing physical workload during manufacturing and logistics tasks. However, these studies reported negative effects on the perceived usability and freedom of movement, concluding that such exoskeletons might be better suited for static activities. In logistics, no significant studies have specifically investigated the application of active exoskeletons (Glock et al., 2021), although the topic is investigated in manufacturing and assembly contexts. Research about active exoskeletons for industrial use mainly focuses on assisting lifting, lowering and static bending tasks. A review summarizes significant reductions of back muscle activity up to -48% during lifting and -12% during bending when using active exoskeletons (Kermavnar et al., 2021). However, feedback about usability and user experience was mixed, with some studies that reported decreased performance and increased perceived task difficulty. While all the reviewed studies consistently assess the physical impact of exoskeletons, often using bio-signals such as EMG, other human factors are less frequently evaluated and always through questionnaires. Perceptual and psychosocial aspects, such as device acceptance, discomfort, frustration, and usability, are typically examined more than cognitive workload.

3. METHODOLOGY

This research adopts an experimental-based methodology to investigate the impact of active exoskeletons in a parts-to-picker system. The aim is to provide empirical insights about the impact of active exoskeletons on human operators, considering both physical, cognitive and perceptual aspects, and picking performance.

3.1 Experiment design

The experiment simulates the adoption of an active exoskeleton during an order picking activity in a parts-to-picker system and compares it with a similar scenario where the supportive technology is not adopted, with different types of handled unit loads. The aim is to study picking performances and operators' physical and cognitive workload in the different scenarios. The independent variables (manipulated variables) are the system (with/without exoskeleton) and the load (2 kg and 12 kg, respectively). The dependent variables are productivity performance metrics, physiological metrics including the cognitive workload and the physical effort, plus the perceived workload. Combinations of the manipulated variables generate four different scenarios (load x2, system x2) in which participants perform the same order picking task during which variables are assessed and compared. To better control for individual extraneous variables, a within-subject experiment design is selected, meaning that each participant performs all 4 tasks (Pasparakis et al, 2023). To eliminate the effect of the execution order, participants perform the different tasks in a randomized order. Twelve male healthy subjects (age: M=29.6 years, SD=4.5; height: M=1.80 m, SD=0.06; weight: M=72.5 kg, SD=8) with no history of low back pain and no experience in order picking participated, on a voluntary basis, in the experiment, which took place at XoLab at the Istituto Italiano di Tecnologia (IIT), Italy, authorized by the Ethics Committee of Liguria (reference number: CER Liguria 001/2019). The experiment simulates an order picking task in parts-to-picker setting, specifically at a picking station with a conveyor (simulated by a shelf, height=1m) delivering boxes. The task involves a picker who must transfer boxes from the shelf onto a pallet according to an instruction sheet. Each palletized unit represents an order, and it is composed of 12 boxes with different dimensions, stacked in two levels of six boxes each. Each task has a duration of 15 minutes during which the participant repeatedly completes a palletized unit load of 12 boxes. The task is repeated by each participant in four different scenarios: with exoskeleton and boxes of 2 kg; without exoskeleton and boxes of 2 kg; with exoskeleton and boxes of 12 kg; without exoskeleton and boxes of 12 kg.

The experimental procedure begins with the participant being informed about the testing protocol and equipment. The participant then signs informed consent and completes a questionnaire with personal data. Electroencephalogram (EEG) and EMG sensors to monitor neurophysiological responses are applied. After sensors setup, the participant receives a detailed task explanation and undergoes a brief training session. Then, there is a three-minute resting period in a seated position, during which EEG recordings were taken to capture baseline bio-signals before the tasks are performed. The experiment comprised four 15-minute tasks, one for each scenario. After completing each task, participants fill out the NASA Task Load Index (NASA-TLX) questionnaire, a widely acknowledged tool commonly used in literature to assess perceived workload (De Lombaert et al., 2023) and undergo a three-minute resting period in a seated position, during which EEG signals are recorded.

3.2 Exoskeleton

The exoskeleton employed in the experiment to assist human operators during the picking task is the XoTrunk, which is an active back-support exoskeleton developed at the IIT in collaboration with the Italian Workers' Compensation Authority (INAIL) for assisting MMH activities. The XoTrunk features control software that automatically adjusts assistance levels to accommodate dynamic tasks involving varying movements and support needs. It uses two electric motors with torque control to generate up to 40 Nm of support in the sagittal plane, aiding hip and back extension (Lazzaroni et al., 2022). Support forces are applied through straps on the thighs and a chest vest, while a lumbar cushion provides added comfort in the device's frame. Thing straps and chest vest are adjustable to fit different body shapes and dimensions. Moreover, the chest vest can be adjusted in height to adapt for individuals ranging from approximately 1.60 m to 2 m in height.

3.3 Data collection and processing

This experiment used three primary data sources: bio-signals measured through biosensors to assess human workload, self-reported metrics assessed through questionnaires to measure perceived workload, and picking productivity measures collected through observation. Bio-signals were collected using biosensors to assess participants' *physical fatigue* and *cognitive workload* across the four different task scenarios. *Fiscal fatigue* has been assessed through the muscular activity of the lumbar muscles, i.e., right and left erector spinae longissimus lumborum (LL) and erector spinae iliocostalis lumborum (IL), acquired with EMG, through surface EMG electrodes (BTS FREEEMG, BTS Bioengineering, Italy). EMG data processing includes band-pass filtering (10-400 Hz), removal of electrical noise, rectification, and low-pass filtering with a 2.5 Hz cut-off frequency. The EMG signals are then normalized to the maximum voluntary contraction (MVC). MVC was recorded prior to data collection during a maximum exertion task, performed three times, where participants must lay prone with their torso extending beyond the edge of a test bench and lift their trunk against manual resistance. *Cognitive workload* is a central concept in human performance research, arising from the observation that our cognitive system has limited capacity for processing tasks (Chikhi et al., 2022). Brain waves, the electrical impulses generated by the brain, play a key role in cognitive functioning, as they transmit information and trigger electrochemical changes (J. Flowers Health Institute). In this experiment, cognitive workload is assessed using EEG that captured brain waves by the cEEGrid (Debener et al., 2015). Specifically, the analysis focused on Alpha brain waves. Alpha activity is highly sensitive to changes in cognitive workload; it shows an inverse relationship with attention and concentration, where focused attention corresponds to suppressed Alpha activity in the contralateral visual cortex and increased Alpha in the ipsilateral visual cortex (Chikhi et al., 2022). EEG data were recorded using the cEEGrid electrode array, a flexible sheet containing ten Ag/AgCl electrodes arranged in a c-shape around the ear. Unlike traditional electrode configurations, the cEEGrid is discreet, comfortable, and requires minimal electrode gel, making it quick to apply and remove (Getzmann et al., 2021). This setup is particularly advantageous for prolonged recordings, as its design-miniaturized wet sensors under a sealing film reduce electrolyte evaporation, helping to maintain signal quality over time. EEG data processing involves band-pass filtering to select Alpha waves and then outlier detection. Then, alpha signals are normalized to the baseline signal recorded before task execution during a three-minute rest. Questionnaires collected self-reported metrics on *perceived workload*. After each task, participants completed the NASA-TLX. This tool questions the effort exerted by individuals during the execution of an activity, providing insight into task difficulty (Agency for Healthcare Research and Quality USA, 2006). The NASA-TLX measures six subscales: mental demand, physical demand, time demand, performance, effort, and frustration, on a 21-point scale. Lastly, *productivity measures*, i.e., time per pallet, were collected through observation. A chronometer measured time, while counts were recorded for each box handled.

3.4 Data analysis

To assess significant differences among the different scenarios, i.e., H_noExo, H_Exo, L_noExo,, L_Exo (H stands for heavy and L for light refers to weight), statistical analyses were performed. A repeated measures Analysis of Variance (ANOVA) was used, followed by paired *t*-tests with Holm-Bonferroni correction as post-hoc analysis. Assumptions for ANOVA were checked via the Shapiro-Wilk test for normality, Levene's test for homogeneity, and Mauchly's test for sphericity; if unmet, Friedman's test and Wilcoxon signed-rank post-hoc were applied with the same correction. A 0.05 alpha level was set. Due to missing data and outliers, EMG analysis was limited to 10 subjects and EEG analysis to 7.

4. RESULTS AND DISCUSSION

4.1 Physical fatigue

Physical effort is studied by analyzing the muscle activity of the LL and IL muscles, captured by the EMG. A first analysis of the muscle activity shows that for each setting (high loads and light loads) and each muscle (LL and IL) the condition without exoskeleton always present the highest average muscle activity, with a more evident difference between the two conditions in the high-loads setting. These results are also stable among the participants. Fig. 1 presents the boxplot for the peak muscle activity (average among all subjects) for LL and IL respectively normalized to MVC.

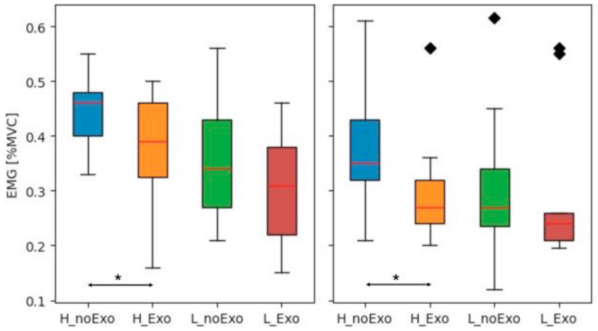

Figure 1. Box plots of the peak muscle activity values of the LL (left) and IL (right) muscles in the four scenarios. Horizontal bars indicate the level of statistical significance (* = p-value <0.05).

Friedman's test was conducted on the muscle activity of both muscles (LL and IL), as the normality of data was not verified for IL muscle. For consistency, the Friedman test was applied to both. The *p*-value of Friedman's test is significant for both muscles (p-value<0.01). Subsequently, the Wilcoxon signed-rank test (with Holm correction) was performed to test pairwise differences among scenarios. For both LL and IL the comparison between H_exo and H_noExo presents a significant statistical difference ($\text{delta}_{\text{noExo-Exo}}=0.063$ p-value = 0.019 and $\text{delta}_{\text{noExo-Exo}}=0.093$ p-value = 0.012, respectively), corresponding to a reduction of muscle activity of 14% and 23% respectively when using exoskeletons in the setting with high loads. No statistical significance emerged in relation to the adoption of the exoskeleton in the setting with light loads (p-value = 0.17 and p-value = 0.25 respectively). This suggests that the physical support that the exoskeleton provides to the operator is more effective when handling heavy loads.

4.2 Cognitive workload

Cognitive workload is analyzed considering the level of attention and concentration, strongly correlated to the Alpha value, i.e., the value associated with the Alpha brain waves detected through EEG. A first analysis of the Alpha value shows that for each setting (high loads and light loads) the condition with exoskeleton always presents the lowest average, meaning that the adoption of an exoskeleton could require the involvement of a higher concentration, with a more evident difference between the two conditions in the high-loads setting. However, the single participants are not always aligned with these results, indicating an expected degree of interindividual differences across participants. Besides, once the hypotheses of normality, homogeneity and sphericity were verified, a repeated measures ANOVA test showed that no significant differences emerged in the mean alpha values of the four scenarios (Fig. 2).

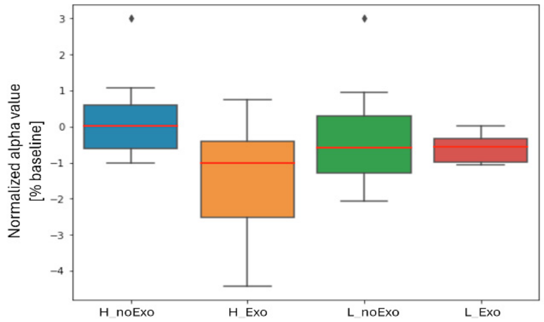

Figure 2. Boxplot of the mean normalized Alpha values in the four scenarios.

4.3 Perceived workload

Perceived workload was studied both to compare the perceived physical and mental effort against the related recorded bio-signals and to assess the human perception of human-technology interaction. To this aim, a survey using the NASA-TLX questionnaire was conducted. The perceived mental demand of users when an exoskeleton is adopted results on average higher than scenarios without an exoskeleton, in line with what emerged from EEG. Friedman test, however, reports a not statistically significant difference among the scenarios.

The perceived physical demand for each setting (high loads and light loads) is on average higher when the task is not assisted. This phenomenon is much more evident for the setting with high loads, in line with the EMG results. No relevant difference (has been found by the paired *t*-Tests with Holm's correction that follows the repeated measures ANOVA analysis performed (p-value < 0.0001).

Analyses of the perceived temporal demand, and perceived performance, self-reported by participants in the NASA-TLX questionnaire, show neither statistical significance in the difference between the two levels of support (i.e., active exoskeleton and absence of exoskeleton), nor a specific common trend related to it.

The perceived effort and perceived frustration do not show statistically significant differences emerging from the performed hypothesis tests. However, some common trends among participants can be identified. As per the perceived effort, instead, in the high loads setting, it appears to be on average higher for the unassisted task. Differently, in the setting with light loads, the perceived effort is on average higher in the task supported by the active exoskeleton. As per the frustration level, instead, it records average higher values when the exoskeleton is adopted for both settings. These results, although they cannot find statistical validation, could find confirmation in some studies that find exoskeletons to limit movements, increase overall effort and cause discomfort according to participants (Cardoso et al., 2020). These results, however, need to be validated in longer studies, as it might also depend on the low level of familiarization with the device. It has been shown that users' perception of a back-support exoskeleton could change within the first 4 hours of use (Favennec et al., 2024).

4.4 Productivity performances

Productivity performance is studied in terms of time per pallet [s/pallet]. A first analysis of the results shows that for each setting (high loads and light loads) the condition without exoskeleton always presents the highest average productivity. These results are also stable among the participants. Fig. 3 presents the boxplot for time per pallet [s/pallet].

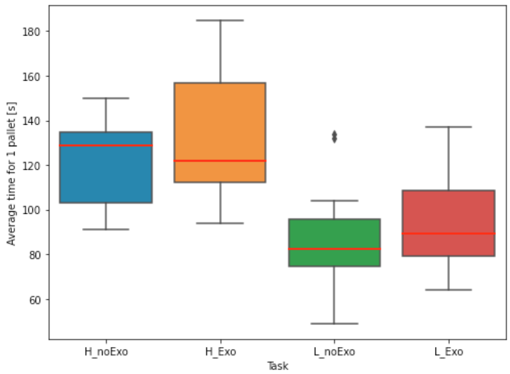

Figure 3. Box plots of the average time to complete one pallet in the four scenarios.

Once the necessary hypotheses were verified, a repeated measure ANOVA test was conducted (p-value < 0.0001), followed by a paired *t*-test with Holm's correction, to test pairwise differences among scenarios, that record significant results ($\text{delta}_{\text{NoExo-Exo}}$= -10.58 s/pallet for high loads corresponding to a 8.7% increase with exoskeleton - p-value < 0.1; $\text{delta}_{\text{NoExo-Exo}}$= -6.92 s/pallet for light loads corresponding to a 7.9 increase with exoskeleton - p-value <0.1). This means that the adoption of exoskeleton can hinder picking productivity. Also in this case, the result should be validated in longer studies, as it might also depend on the low level of familiarization with the device.

5. CONCLUSION

The paper advances the understanding of assistive technologies in warehousing by focusing on human-machine interaction in picking activities, situating itself within the evolving Warehousing 5.0 paradigm. Specifically, it examines the impact of an active exoskeleton in parts-to-picker tasks, comparing assisted and unassisted scenarios. The study evaluates task performance and human well-being, addressing physical, cognitive, and perceived workload across varying operational conditions, including different unit loads. Data collection methods included observation, questionnaires, and bio-signals (EMG and EEG). The study provides important academic and managerial contributions by exploring underexamined topics such as the adoption of active exoskeletons for picking activity, the assessment of the cognitive impact, measured through bio-signals, alongside the physical one, the assessment of exoskeleton adoption comparing different settings (e.g., different types of unit loads handled). Results indicate that this active exoskeleton reduces muscle activity. The reduction is more pronounced for heavy weights, while lighter loads show minimal benefit and even increased perceived effort. These findings suggest the device utility is task-specific, with greater advantages in high-strain scenarios. Cognitive workload, assessed through EEG and NASA-TLX, revealed no significant differences between assisted and unassisted tasks, though participants reported higher mental demand and frustration with the exoskeleton. Productivity metrics consistently favored unassisted tasks, with performance declines more pronounced for lighter weights. The study aligns with existing literature, confirming the muscular benefits of exoskeletons and noting productivity declines. These limitations may stem from discomfort and restricted movement reported by participants, or limited user familiarity with the device, which prior research suggests could improve after extended use (Favennec et al., 2024). Furthermore, the study offers relevant insights for companies considering exoskeleton adoption in picking tasks, analyzing trade-offs between productivity and human well-being in different conditions. While a pure male sample has been selected to assure consistency within the small sample tested, a larger and more heterogeneous sample would enable further observations such as the variation of the studied effects according to human characteristics (such as gender, age, weight), thus improving generalizability of the results. Future research should expand the participant groups to enable more robust statistical analyses. A larger sample would allow to control the results on the height of the picking station, on the pace kept by participants during the task, and on the execution sequence of the 4 conditions. Besides, longer experiments could uncover more nuanced effects, such as variations in performance, physical and mental fatigue over time, and the effect of familiarization with the device, potentially revealing improvements in both usability and productivity as users become more accustomed to the technology.

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