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Cold storage, warm breaks: The effects of rest breaks on order picking performance in cold-storage environments

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ABSTRACT

Cold-storage systems are essential components of cold supply chains. Although order picking technologies have advanced, many of these systems still rely on human labour, where workers are exposed to temperatures below −20 °C. Despite wearing protective clothing, prolonged exposure to such cold conditions can lead to cold stress, causing physiological impairments and fatigue, which ultimately reduce performance. Warm rest breaks are crucial to mitigate these adverse effects and maintain productivity. However, there is a dearth of field evidence on the effect of the timing and duration of these breaks on order picking performance. To address this gap, we collaborated with a grocery retailer to examine the impact of rest-break durations on the performance of order pickers in a cold-storage environment set at −21 °C. We analysed 514,953 visits to storage locations by 40 order pickers over four months, using a multilevel model with random intercepts and slopes. Our findings revealed a horizontal S-shaped relationship between work time after a break and order picking time, characterised by an initial increase, a stabilisation period, and then a sharp increase. The results suggest that there is an optimal working period following a rest break during which performance peaks before it begins to decline. This period varies depending on the length of the break, highlighting the importance of strategic scheduling to maximise order picking efficiency in cold-storage environments.

1. Introduction

Order picking (OP), which is the most labour-intensive and costly activity in warehouses, is crucial for maintaining an efficient logistics system (Grosse, 2024). This process, which often accounts for up to 55% of the total warehouse operating expenses, directly affects customer satisfaction and the operational efficiency of warehouses (Setayesh et al., 2022). The growing complexity of supply chains and the increasing customer demand for rapid delivery have further emphasised the importance of OP performance, which is often assessed based on OP time.

Despite the technological advancements attributed to Industry 4.0, such as robot picking systems, manual OP remains a critical and irreplaceable component of warehouse operations, owing to the high flexibility of human workers (Winkelhaus et al., 2021; De Lombaert et al., 2023; Grosse, 2024). This necessitates the prioritisation of integrated works that focus on human factors and performance in OP (Grosse et al., 2015, 2017; Vijayakumar et al., 2022). Our research contributes to this knowledge base by empirically examining how breaks impact OP performance in cold-storage environments operated below −20 °C. This investigation is crucial because despite the recognised need for warm breaks to mitigate the effects of cold stress, field studies on these breaks—particularly the impact of their duration and scheduling on OP performance—are lacking in the existing literature.

The investigated OP in cold storage is a special scenario wherein the order pickers pick frozen food items stored in artificial cold environments at −21 °C. These items include seafood, meat, vegetables, fruits, ice creams, and ready-to-eat and ready-to-cook meals. According to a market survey by Fortune Business Insights (2021), the worldwide market for frozen foods was valued at nearly 300 billion USD in 2023 and is projected to grow by approximately 41.94% from 2024 to 2032. Hence, the improvement of OP operations in cold-storage warehouses and distribution centres is critical.

Previous studies have shown that in general, working in cold

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temperatures adversely affects the performance of workers. Pilcher et al. (2002) concluded that variables such as the length of exposure to the cold, the duration before task onset, the type of task, and the duration of the task can influence this relationship and potentially modify how temperature impacts performance. Cold stress, as detailed by Holmér (1994) and Holmér et al. (2012), arises from an imbalance in body heat regulation, which leads to fatigue and performance decline. Moreover, the substantial temperature gap between the inside and outside of cold storage, which could exceed 50 °C during the summer, could place significant stress on workers (Morioka et al., 1998) which may affect their performance.

Physiological studies have indicated that working in cold-storage environments significantly lowers both the core and skin temperatures (Baldus et al., 2012; Kluth et al., 2012). Although a bulky protective gear provides insulation, it also increases physical strain, resulting in a higher heart rate (Kluth et al., 2012). Blood pressure also increases with prolonged exposure to cold (Morioka et al., 2005), and over 60% of workers typically report issues such as nasal discharge and cold or painful hands. Seasonal variations amplify these effects, particularly during winter (Morioka et al., 2005). In addition to these physiological considerations, Grosse et al. (2015) highlighted that cold-work environments can induce additional psychological stress on order pickers compared to room-temperature ones. Therefore, OP in cold storage creates unique challenges in addition to the physical, cognitive, perceptual, and psychosocial demands (Grosse et al., 2015, 2023) associated with OP at room-temperature.

Implementing intra-work breaks is a crucial strategy to facilitate recovery from physically demanding work and to enhance both the productivity and reliability of workers (Battini et al., 2017; Di Pasquale et al., 2017; Glock et al., 2019; Darwish, 2023). In addition, such breaks offer psychosocial benefits, improve social relationships in the workplace, enhance worker satisfaction, and induce alertness-enhancing effects (Tucker, 2003). Xu and Hall (2021) emphasised the significant impact of strategically planned work–rest schedules on reducing fatigue and enhancing productivity across various work environments.

Although work–rest scheduling has been discussed in OP-related literature (Casella et al., 2023; Rijal et al., 2021; Zhao et al., 2019), to the best of our knowledge, no field studies have examined the real-world implications of rest breaks on OP performance in cold-storage environments. In this paper, we present the results of a real-world study wherein data from a storage facility in Germany operating at −21 °C were collected and analysed. Our research aimed to address the following two questions.

(1) How does the OP performance in cold-storage environments vary between breaks?
(2) How does the break duration influence post-break OP performance?

The remainder of this paper is organised as follows. Section 2 discusses the relevant studies highlighting the research gap and the contribution of this investigation. Section 3 explains the empirical settings and data employed in this study, and Section 4 elucidates the variables and modelling process employed. Section 5 presents and discusses the results of the analysis. Finally, Section 6 summarises the main findings of the study and considers potential future research.

2. Literature review

In this section, we begin with a broad overview of work–rest balance research in industrial settings. Next, we discuss the current state of the art in work–rest research in the context of OP. We then present a synthesis of existing research on work–rest practices in OP related to cold-storage environments, followed by a discussion of the contributions of our study.

2.1. Work–rest balance at work

Work–rest scheduling can effectively prevent work-related fatigue, which can significantly affect the normal functioning of the body, with effects on the cardiovascular system, skeletal-muscular system, and the brain and consequently, worker performance (Konz, 1998). Work–rest scheduling requires the strategic allocation of breaks within work shifts to facilitate recovery, ensuring a balance between productivity and the health and safety of workers by optimising the frequency, timing, and length of breaks (Xu and Hall, 2021). Tucker (2003) highlighted that the effectiveness of rest breaks on worker performance and recovery is also influenced by the specific characteristics of the job and individual worker's needs. Accordingly, they highlighted the importance of allowing workers to identify and address their fatigue levels (i.e. self-regulation of breaks). However, there is conflicting evidence on whether self-determined or pre-planned rest breaks are more effective. They also noted that the optimal timing of rest breaks should consider job routines and the effects of start-up and shutdown procedures on efficiency and accident risks.

Early theoretical and computational models aimed at predicting the impact of various work–rest schedules on worker performance, health, and safety emerged with Eilon's 1964 model, which focused on determining the optimal length and timing of a single break to maximise productivity (Bechtold and Thompson, 1993; Darwish, 2023). Since then, various models have been developed that simulate various scenarios and their outcomes based on factors such as work intensity, shift duration, break times and durations, and physical and cognitive demands of tasks (Xu and Hall (2021)). Bechtold (1991) categorised recovery during rest breaks into five types: (1) less than full recovery, (2) exact full recovery, (3) inexact full recovery, (4) at most full recovery, and (5) full recovery. Understanding these recovery categories could be instrumental in designing work–rest schedules tailored to the specific recovery needs of workers.

2.2. Work–rest literature in OP context

Previous studies have noted that fatigue elevates error rates among OP workers (Setayesh et al., 2022) and, consequently, increases the likelihood of accidents or injuries (Battini et al., 2017; Di Pasquale et al., 2017). Therefore, determining a rest allowance (RA) in OP is important for establishing the amount of time required for an operator to fully recover (Battini et al., 2017). Researchers have developed different RA models to support decision-making in OP. For instance, Battini et al. (2016) combined human energy expenditure in OP and the storage assignment problem as a bi-objective optimisation problem and integrated RA using Price's (1990) RA formulation. They showed that although a time-based storage-assignment policy may optimise the efficiency of OP processes, it can result in increased fatigue among pickers owing to higher energy expenditure. Conversely, an energy-based storage-assignment policy might increase the OP time, but it benefits the pickers by reducing oxygen consumption, fatigue, and the amount of RA needed. Therefore, Battini et al. (2016) emphasized the importance of considering multiple objectives, not just time efficiency, when designing storage-assignment policies to achieve a more balanced and sustainable operational approach. Battini et al. (2017) proposed a model for evaluating manual OP systems, focusing on the additional ergonomic effort required by human operators by integrating two key concepts: human availability and RA. Human availability refers to the proportion of time during which workers can perform their tasks effectively without being hindered by physical or mental limitations while RA quantifies the necessary downtime required to maintain health and productivity, based on the ergonomic strain imposed by picking activities. Elbert and Müller (2017) investigated how the common assumption in OP planning models—that pickers travel at a constant velocity throughout the warehouse—compares to the realities of navigating curves and performing turning manoeuvres across aisles. They explored the impact of these factors on travel time and energy expenditure, and consequently, on RA. Sgarbossa and Vijayakumar (2020) developed an RA model that considered the age of pickers.

These RA models provide a quantitative basis for determining the necessary amount of rest based on ergonomic assessment, which then contributes to improved work–rest scheduling to create an effective and practical solution for workers.

However, none of these RA models have focused on OP in cold-storage environments. The next section discusses work–rest-related studies involving OP in cold storage.

2.3. Work–rest-related research in cold storage

Field experiments have consistently demonstrated that working in cold-storage environments, such as at −24 °C, induces significant physiological changes in order pickers, including reductions in core and skin temperature. Table 1 summarises the results of our literature review on work-rest-related research in cold-storage environments and the contributions of our study, which focuses on the impact of rest breaks on OP performance. Among them, Kluth and Strasser (2008) measured the physical strain on order pickers in cold-storage environments by examining their cardiovascular system, specifically heart rate and blood pressure. They found that more experienced order pickers managed physical strain better during a work shift than less experienced ones.

In field experimental studies, Kluth et al. (2009, 2013) investigated the effects of working in different temperatures on male order pickers of varying ages: one group in a chill room at +3 °C and another in cold storage at −24 °C during a work shift. Their workday included three work sessions lasting 80, 100, and 120 min, each separated by 20-min warm-up breaks at +21 °C. They categorised pickers into two groups based on their age: younger (20–35 years) and the older (40–65 years). Both studies reported a significant decrease in core temperature across both age groups in both environments, whereas no age-related skin temperature differences were reported for most measuring positions. However, Kluth et al. (2013) suggested that older pickers experience a substantially higher strain than younger pickers. Penzkofer et al. (2009) examined a male order picker sample in a considerably longer experimental study (75 workdays) for the same work–rest schedule setting in both a chill room and cold storage. During shorter work phases (80 and 100 min), the heart rate of the older group varied significantly compared to that of the younger group. However, no significant age-related differences in the longest work phase were observed (120 min).

Kluth et al. (2012) and Baldus et al. (2012) conducted similar field experiments with only female order pickers. The latter study reported that female pickers in both environments experienced a decrease in their core-body temperature. However, those in the chill room group managed to recover during their 20-min warm-up breaks regardless of age. By contrast, those in the cold-storage group did not fully recover, regardless of their age. Although their skin-surface temperature was maintained in the chill room, it significantly decreased in cold storage, especially at the extremities, including at the nose, fingers, and toes, leading to discomfort. Baldus et al. (2012) noted that older female workers experience larger decreases in core-body temperature under such conditions. Kluth et al. (2012) reported interesting variations compared with the observations made by Kluth et al. (2013). Although the 2012 study anticipated notable differences between age groups, these were not evident among female order pickers. This finding implies that other elements, such as individual fitness and heart-rate capacity (i.e. maximum heart rate calculated as $HR_{max} = 208 - (0.7 \times \text{age})$ (Tanaka et al., 2001)), significantly influenced the outcomes in this group.

In a later study, Groos et al. (2019) conducted a similar field experimental study in cold-storage environment with a sample size of 60 comprising both male and female order pickers. They observed a significant decrease in the core-body and skin-surface temperatures at the fingers, toes, and nose. The results from the subjective assessments by the pickers confirmed these temperature reductions, reinforcing the findings of their physiological measurements.

Overall, these experimental studies confirmed the importance of considering individual worker characteristics when assessing the physiological impact of working in cold-storage environments.

2.4. Research gap and contributions of this study

Existing RA models, as discussed in Section 2.2, overlook the unique physical and mental strains posed by cold-storage conditions. In these environments, cold stress intensifies fatigue by increasing the metabolic rate, which in turn increases the rest requirements. Although the experimental studies detailed in Section 2.3 examined the physiological impacts on order pickers in cold-storage environments, they did not assess how specific work–rest schedules influence OP performance in real-world settings. Our study addresses these gaps by empirically investigating the impacts of rest breaks OP performance in cold-storage environments in real-world scenarios. Our results offer operational and behavioural insights into break-taking, such as optimal timing and duration, and the impact of fatigue progression on OP performance.

From a theoretical standpoint, empirical results regarding the impact of rest-break schedules and their durations on OP performance in cold-storage environments are valuable for extending RA models and defining work–rest optimisation problems. These insights can not only improve OP performance but also ensure worker safety and well-being. From a managerial perspective, this information is beneficial for warehouse managers as it can influence how operations are structured to balance efficiency with workers' needs in harsh working environments via optimised work–rest schedules. Additionally, our dataset reflects the natural behavioural patterns of order pickers in cold-storage environments when rest breaks are taken without any intervention (i.e., observational effects). This facilitates the identification of organic patterns that can inform better scheduling policies and decisions without disrupting their natural workplace behaviour.

3. Methodology

3.1. Empirical settings and data description

In this field study, we investigated the impact of rest breaks on OP performance in cold-storage environments. To address the research questions, we collected real-world data from a brick-and-mortar grocery retailer warehouse which operates as a picker-to-part OP system. We focused on a single warehouse located in Germany that stored and processed frozen food products at −21 °C. At any given time, the 5,500 m^2 facility had a total inventory of approximately 1,700 items and processed 30,000 items on average per day. As illustrated in Fig. 1, pickers equipped for cold environments gathered items from storage and placed them in ice-pack-equipped insulated roll cages ('load units'), which were attached to industrial trucks. A digital assistive device (i.e. a tablet) was mounted on the truck to provide the picker with information regarding the order items, their storage locations, and other relevant details. These devices maintain a continuous wireless connection to the Warehouse Management System (WMS), enabling real-time documentation of all order picker activities. For the field study, we collected OP data from the WMS between May and August of 2023, resulting in a dataset comprising 514,953 storage location visits by 40 order pickers.

All pick-up locations were at ground level and arranged to facilitate a U-shaped travel pattern. The OP process comprised several sequential steps, which began with travelling to the storage location where the items were stored. Upon arrival, the workers reached and bent to access the storage locations, which involved physical manoeuvring to retrieve the items. After picking the items, they were documented on the WMS using a tablet device. The items were then sorted and stacked in a load unit. The cycle was completed by proceeding to the next pick location according to the order. This process was repeated until all the items in the order were picked and prepared for shipment at the loading bay.

Table 1
Summary of studies on work–rest schedules for OP in cold-storage environments.

Reference	Independent variables					Type of field study (Experimental/ Observational)	Measurements type (Subjective/ Objective)	Dependent variables					Duration of the experiment	Work-rest schedule adopted	Control variable (s)	Results discussed
	Gender		Age	Experience level	Chill room (+3 °C)			Skin surface temperature	Core body temperature	Blood pressure	Heart rate	Energy expenditure				
	Male	Female														
Kluth and Strasser (2008)	7	5		✓		Experimental	Objective			✓	✓		1 work shift	No fixed schedule		Cardiovascular system (heart rate, BP)
Kluth et al. (2009)	30	0	✓		✓	Experimental	Objective	✓	✓	✓	✓		1 work shift	80, 100,120 min separated by 20 min warm-up breaks		Temperature (Skin, Core)
Penzkofer et al. (2009)	30	0	✓		✓	Experimental	Both	✓	✓	✓	✓	✓	75 workdays	80, 100,120 min separated by 20 min warm-up breaks		Cardiovascular system (heart rate, BP)
Kluth et al. (2012)	0	30	✓		✓	Experimental	Both	✓	✓	✓	✓		1 work shift	80, 100,120 min separated by 20 min warm-up breaks	Average workload 1.6 tons to pick per hour (8 tons per shift)	Cardiovascular system (heart rate, BP, Heart capacity utilization)
Baldus et al. (2012)	0	30	✓		✓	Experimental	Objective	✓	✓				1 work shift	80, 100,120 min separated by 20 min warm-up breaks	Average workload 1.6 tons to pick per hour (8 tons per shift)	Temperature (Skin, Core)
Kluth et al. (2013)	30	0	✓		✓	Experimental	Objective	✓	✓	✓	✓	✓	1 work shift	80, 100,120 min separated by 20 min warm-up breaks	Average workload 1.6 tons to pick per hour (8 tons per shift)	Cardiovascular system (heart rate, BP, Heart capacity utilization) Temperature (Skin, Core)
Penzkofer et al. (2013)	62	66	✓		✓	Observational	Subjective	[a]NA								Ratings
Groos et al. (2019)	30	30	✓			Experimental	Both	✓	✓	✓	✓	✓	1 work shift	80, 100,120 min separated by 20 min warm-up breaks	Average workload 1.6 tons to pick per hour (8 tons per shift)	Temperature (Skin, Core)
This paper	40	0				Observational	Objective	OP time					4 months	Company work-rest schedule	Travel distance, Item weight, Item volume, Pick density	OP time variation between breaks and impact of duration of the break on OP time

[a] NA – Not Applicable.

Fig. 1. OP in the cold-storage warehouse operating at −21 °C.

The data set we used was an archival dataset provided by the partnering firm from their WMS to empirically investigate the impact of break duration and time after break on OP time. The WMS captures detailed log data of OP operation and includes a wide range of information, including batch-ID, pick-ID, and picker-ID to identify human–robot and human–manual configurations, timestamps marking the start and end of each individual task, quantity of SKUs picked, weight and volume per SKU, and the location. Although the actual travel path of the picker was not observed, the minimum travel distance was calculated based on the storage locations and physical layout of the rows and cross aisles using a modified version of urban geometry. This form of geometry assumes that travel can only occur in a grid pattern, which was formed by the aisles and cross aisles between the storage racks in this study.

We used the timestamps from the archival WMS data to calculate the break duration for each of the 40 pickers. The company policy mandates two standard rest breaks of 20 and 40 min per work shift. Additionally, order pickers were offered an extra 30 min of paid warm-up breaks, which could be distributed as needed to manage cold stress. Pickers had the flexibility to divide this extra 30 min across their two standard breaks to ensure equality. This flexibility explains the observation of breaks in the data for up to 60 min (see Fig. 2(a)). Alternatively, they could have opted to take a separate third break of 30 min. However, given the mandatory nature of these breaks, we accounted for total break duration in our analysis. Although fixed rest breaks were standard, the additional flexibility provided by the warm-up breaks allowed us to incorporate individual preferences into break-taking behaviour.

3.2. Model formulation and variables

3.2.1. Notations

i	Storage location
j	Order picker
α_{0j}	The intercept term for the jth picker for individual baseline OP time.
ϕ	Fixed effects of picking and stacking height
τ	Fixed effects of time-related order quantity variations
ε_{ij}	Error term for the ith storage location visited by the jth picker, accounting for unexplained variability.
γ_{00}	Overall mean intercept across all order pickers.
υ_{0j}	Random effect for the jth picker, capturing individual deviations from γ_{00}.
γ_{10}	Average effect of the interaction between break duration and time after break across all order pickers.
γ_{20}	Average effect of time after break across all order pickers.

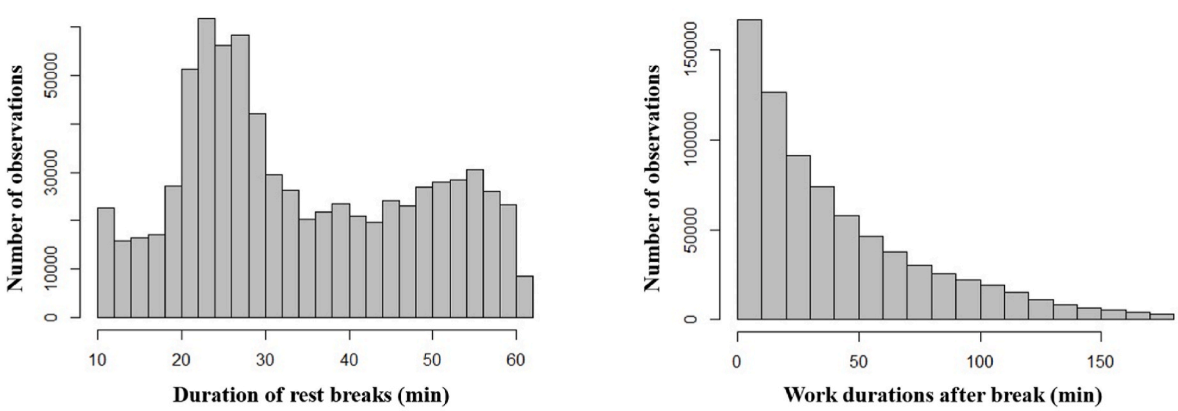
3.2.2. Dependent variable

In this study, we analysed the order pickers' performance by measuring the OP time required to complete the OP cycle, as described in Section 3. Specifically, we measured the seconds elapsed between consecutive storage points—from one location to the next (*i-1* to *i*)—for each picker (*j*), treating it as a continuous variable. On average, the OP cycle took 20.12 s, with a standard deviation of 18.11 s (see Table 2 for descriptive statistics).

3.2.3. Independent variables

To assess the impact of rest-break duration on OP performance, specifically the OP time, we analysed the durations of rest breaks, which averaged to 27.07 min with a standard deviation of 18.11 min, as listed in Table 2. This average represents the rest-break duration of an order picker during a shift, including both scheduled and unscheduled breaks, in accordance with the work–rest policy of the warehouse. Fig. 2(a) presents the distribution of break durations in our dataset, which reveals the break-taking behaviour of pickers in the cold-storage warehouse. Notably, most rest breaks are within the 20–30 min. Overall, Fig. 2(a) indicates that the break duration distribution was inconsistent, highlighting that, although there were common break durations, the break lengths of the pickers varied significantly.

To explore the impact of break duration on post-break OP performance and assess the performance variations between breaks (RQ1 and RQ2), we introduced a variable called *time after break*, which represents the time of active work that an order picker engages in between rest breaks. The average of time after break was 39.62 min with a standard deviation of 35.71 min. This interval began immediately after an order picker resumed work, as identified by their first visit to a storage



(a) (b)

Fig. 2. Distributions of independent variables in the data. Distributions of (a) break durations and (b) work times between breaks.

Table 2
Descriptive statistics of the variables employed in this study.

Variables	Minimum	1st Quantile	Median	Mean	3rd Quantile	Maximum
OP time (s)	2.00	10.00	15.00	20.12	24.00	239.00
Time after break (min)	0.02	11.15	28.10	39.63	58.95	150.00
Break duration (min)	10.02	21.53	26.12	27.07	32.80	44.98
Travel distance (m)	2.40	2.40	4.80	17.08	12.00	149.40
Item weight (kg)	0.24	2.72	3.51	4.35	5.01	31.39
Item volume (L)	0.83	9.98	12.74	14.06	17.45	29.50
Pick density (Number of items picked from one location)	4.00	6.00	8.00	9.10	10.00	28.00

location after a break using the WMS logs, and ended when the picker began their next break. Fig. 2(b) illustrates the distribution of the *time after break* data within our sample, which reveals a decreasing and right-skewed pattern. This indicates that shorter work periods following rest breaks are more prevalent than longer work periods. By monitoring the duration of work after the breaks, we aimed to explore workers' post-break work rhythms and activities. This analysis offers insights into the effects of the duration of breaks on subsequent work performance and the overall pace of the pickers.

3.2.4. *Control variables*

For analysing OP time, it is important to account for variables that may complicate the relationships of interest. First, we incorporated controls for *item weight* and *item volume*, recognising them as relevant characteristics that can significantly influence picker performance.

Next, the travel distance was identified as a key factor as our dependent variable included the time spent by the order picker to navigate from one storage location to the next. The distance between the picking locations significantly influenced the OP time as a longer travel distance may increase the OP duration. In addition, we introduced the pick density variable to control the number of items retrieved from a storage location. Pick density represents the frequency of picks per storage location and is known to significantly influence product characteristics such as colour (Hanson et al., 2018). A higher pick density could imply a higher retrieval frequency, which may in turn affect the ease and speed of the OP process, especially when coupled with other products and packaging characteristics.

We further introduced a fixed effect of storage place, referred to as ϕ, to account for the *height* at which the picking and stacking activities occur. Height is an essential component as it entails varying levels of physical effort and ergonomics, which can impact OP performance. Furthermore, by introducing the time-fixed effect variable, τ, we aim to control temporal fluctuations, such as seasonal changes in the order quantities of retail stores. This ensured that our analysis accurately reflected the effects of the examined variables while isolating the influence of time-related factors. This methodological approach enhances the robustness and generalisability of our findings, providing a clear understanding of how the interactions between break duration and time after break affect OP time. Table 2 summarises the descriptive statistics for all the variables included in the econometric model, offering insights into the distribution and range of each variable. For instance, the median OP time was 15 min, which was lower than the mean of 20.12 min, indicating a right-skewed distribution, as discussed in Section 4.3. The first quartile was at 10 min and the third quartile was at 24 min, indicating that 50% of the OP times are distributed between these two values.

3.2.5. *Econometric model*

We adopted a longitudinal design based on the data in which the OP time for each picker was tracked across multiple points during the study period. Standard linear regression models assume that each data point is independent, which is not valid for our repeated measures. Therefore, we used a multilevel model, also known as a hierarchical or mixed-effects model, which can handle multiple observations of the same individuals without artificially inflating the estimates. Our base model is expressed as follows:

$$\begin{aligned} Order\_Picking\_Time_{ij} = {} & \alpha_0 + \beta_{1j}\, Break\_duration_{ij} + \beta_{2j}\, Time\_after\_break_{ij} \\ & + \beta_{3j}\, Item\_volume_{ij} + \beta_{4j}\, Item\_weight_{ij} \\ & + \beta_{5j}\, Travel\_distance_{ij} + \beta_{6j}\, Pick\_density_{ij} + \phi + \tau \\ & + \varepsilon_{ij} \end{aligned} \tag{1}$$

$$\alpha_{0j} = \gamma_{00} + \upsilon_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} \tag{3}$$

$$\beta_{2j} = \gamma_{20} \tag{4}$$

To develop the multilevel model, we differentiated between fixed effects, which were consistent across individuals, and random effects, which varied among them. To quantify the extent to which the variation in the OP time was caused by inter-picker differences (as opposed to intra-picker differences over time), we calculated the intraclass correlation coefficient (ICC) using a model without predictors. The ICC value was 6.20% for the pickers, indicating that a significant amount of the variance in the OP time was due to the differences between them. The remaining variance was owing to intra-picker variability over time. This also justifies the use of a multilevel model that can include random effects to account for the variability between order pickers.

Given that we observed meaningful differences within and between the pickers, we used a multilevel model with 'random intercepts'. This allowed us to account for individual picker differences, represented by a unique random intercept for each picker (*j*). Thus, the model could adjust to the unique baseline performance of each picker owing to inherent individual differences.

In addition to the random intercepts, we added random slopes, which facilitated the estimation of the individual effects of certain factors such as the rest-break duration and the time spent picking orders after breaks, which varied among the pickers. For instance, some pickers may benefit more from longer rest breaks than others. Therefore, we allowed random slopes in the break duration (Eq. (3)) and time after break (Eq. (4)). By including random slopes, we aimed to capture the heterogeneous effects of break duration and the time after break on OP time to further elucidate the dynamics of the OP process in cold-storage environments.

Finally, error ε_{ij} represents the unexplained variance in the OP time for picker *j* at storage location *i*. This included variations not accounted for by the established fixed effects, random intercepts assigned to each order picker, and random slopes associated with variables such as break duration and work duration post-break. This term reflects the unique individual discrepancies between the actual observed OP times and those predicted by the model. We assumed that these error terms were normally distributed with an average of zero, $\varepsilon_{ij} \sim N(0, \sigma^2)$. This implies consistent variance across all data points. This assumption of homoscedasticity (i.e. constant variance) and independence among the residuals, is critical for the reliability and accuracy of the proposed model's predictions.

To ensure the reliability of our econometric model, we thoroughly examined the relationships between all the variables by calculating the variance inflation factors (VIFs) for each variable. The VIFs allowed us to determine whether the utilised variables were too closely related, which is known as multicollinearity. A high VIF value indicates that a variable is heavily influenced by others, which reduces the accuracy of the model's estimations. However, the highest VIF value of 2.9 was obtained for the '*item weight*' variable, suggesting that multicollinearity did not significantly affect the accuracy of the model (detailed results are presented in Table A1 in the Appendix).

For data analysis, we used the RStudio Cloud platform, which we configured using four processing cores and 16 GB of memory, along with the lme4 (Bates et al., 2023) and multilevel (Bliese et al., 2022) packages.

4. Results and discussion

4.1. Base model: impact of control variables on OP time

Initially, we employed a base model to better understand the factors influencing the OP time in the cold-storage warehouse. The results are summarised in the Model 1 column in Table 3, wherein significant positive relationships between travel distance, pick density, and OP time can be observed. This indicates that long travel paths and high pick densities are associated with increased OP times, as described in Section 4.4. For example, the OP time increased by 0.64% when the travel distance increased by one unit. Note that although the positive estimator is 0.006401, the OP time is logarithmic, requiring a log transformation with e^{β}. Conversely, the item volume exhibited a negative correlation. This suggests that picking tasks involving large volumes reduce the picking time. By incorporating fixed effects for place, aisle, and time, we accounted for the unobserved heterogeneity across these factors, thereby refining our estimation accuracy. The significance of the intercept confirmed that the baseline OP time was independent of the considered variables. This base model not only offers meaningful insights but also establishes a comparative platform for subsequent models with higher complexity, which facilitates the examination of the incremental effects of additional variables and interactions on the OP time.

4.2. OP time between breaks

Building on the base model, we incorporated key independent variables—time after break and duration of these breaks—into the analysis. Table 3 presents the results of the multilevel models. Transitioning from the base Model (1) to the enhanced Model (2) resulted in a notable decrease in both the Akaike information criterion (AIC) and Bayesian information criterion (BIC) values; for instance, the AIC value decreased by 192 (i.e. from 983,202 to 983,010) and the BIC value decreased by 147 (i.e. from 983,313 to 983,166) (see Table 3). This indicated an enhancement of the explanatory power of the model. Evidently, the time elapsed after break significantly increased the OP time linearly, whereas the break duration did not have a statistically significant effect. To explore the possibility of a nonlinear relationship, we introduced quadratic and cubic terms for the time after a break in Models (3) and (4), respectively. These modifications further reduced the AIC and BIC values, indicating a progressively better fit of the model to the data.

Model (3) exhibited an inverted U-shaped relationship between the time after break and the OP time, as indicated by the positive and significant effect of the linear term (0.001207) and the negative and significant effect of the quadratic term (−0.000007). It was therefore concluded that after a rest break, each minute spent in the warehouse increased the OP time but with smaller increments of $e^{(0.01207\text{-}0.000007)}$, resulting in an increment of 1.2063%. Thus, the positive coefficient of the linear term indicates that the OP time increases initially as the time spent in cold storage increases after a break, and the negative coefficient of the quadratic term indicates that this increase eventually plateaus and then starts decreasing, producing the inverted U-shaped curve characteristic of a quadratic relationship.

In Model (4), the introduction of a cubic term (which involves increasing the time after break by a power of three) indicated a more complex horizontal S-shaped relationship. This means that after a rest break, the OP time initially increased, and thereafter, the rate of increase was lower (top of the 'S'), and eventually started increasing again at a faster rate (bottom of the 'S'). Although this horizontal S-shaped curve was significant, the impact of the cubic term was low, suggesting subtle changes in the relationship dynamics.

Fig. 3(a) illustrates the horizontal S-shaped relationship of the logarithm of the OP time plotted against the time after break using Model (4). The OP time initially increased until it reached approximately 45 min on the 'time after break' axis. Beyond this point, the OP time did not change significantly until approximately 100 min. Subsequently, the OP time began to increase sharply, completing the horizontal S-shaped pattern. This visualisation helped us to understand the impact of break time on OP performance across various post-break intervals.

Table 3
Results of multilevel regression analysis.

Dependent variable: OP time				
	Model (1) Base model	Model (2) IV model	Model (3) Quadratic IV model	Model (4) Cubic IV model
Independent variables				
Time after break^3				0.0000002*** (0.00000002)
Time after break^2			−0.000007*** (0.000001)	−0.000041*** (0.000003)
Time after break		0.000373*** (0.000116)	0.001207*** (0.000131)	0.002858*** (0.000197)
Break duration		−0.000137 (0.000104)	−0.000134 (0.000104)	−0.000139 (0.000104)
Control variables				
Travel distance	0.006401*** (0.000027)	0.006407*** (0.000027)	0.006409*** (0.000027)	0.006411*** (0.000027)
Item weight	0.011559*** (0.000489)	0.011509*** (0.000489)	0.011519*** (0.000489)	0.011562*** (0.000489)
Item volume	−0.002049*** (0.000192)	−0.002024*** (0.000192)	−0.002019*** (0.000192)	−0.002019*** (0.000192)
Pick density	0.015123*** (0.000265)	0.015065*** (0.000265)	0.015055*** (0.000265)	0.015035*** (0.000265)
Fixed effects				
Storage place	Included	Included	Included	Included
Aisle	Included	Included	Included	Included
Time	Included	Included	Included	Included
Intercept	2.52***	2.54***	2.52***	2.51***
Observations	514,953	514,953	514,953	514,953
AIC	983,202	983,010	982,919	982,847
BIC	983,313	983,166	983,087	983,025

Note: Standard errors are reported in parentheses. *, **, and *** indicate significance at the 0.1%, 0.05%, and.
001% levels, respectively. IV = Independent variables.

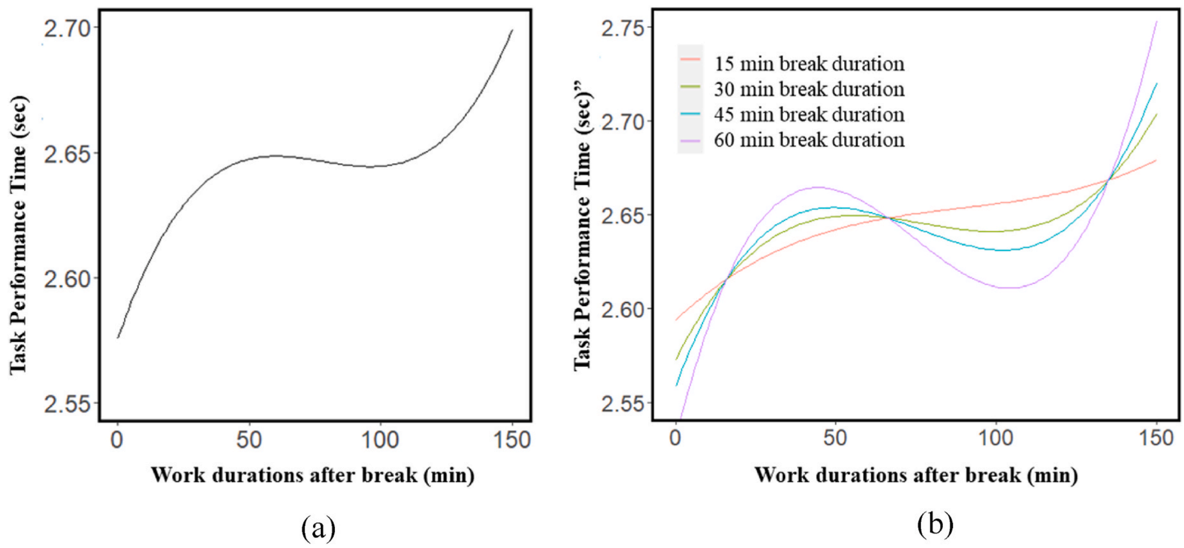


Fig. 3. S-shape behaviour of OP time. (a) S-shape variation in OP time after a break; (b) the moderating effect of break duration on OP time.

4.3. Moderating effects of break duration on OP time

Thereafter, we analysed the effects of break lengths on the relationship between time after breaks and OP time by introducing interactive terms in the model. The interaction between break duration and time after break across all three forms (linear, quadratic, and cubic) was statistically significant. Both AIC and BIC values decreased slightly (by 25 and 23, respectively) compared to those of Model (4), suggesting that this model, with the moderating effect of break duration, fitted the data better. This implies that the effect of time after a break on the OP time is influenced by the length of the break. For example, the impact of time after break on the OP time might vary between short and long break periods.

Fig. 3(b) shows a horizontal S-shaped curve that maps the relationship between the time after break and the OP time, with curves plotted for break durations of 15, 30, 45, and 60 min. The three phases are visible in all the curves. As shown in Fig. 3(b), the 15-min break duration curve is flat throughout, suggesting that shorter breaks had a consistent but minimal impact on OP performance. In contrast, the 60-min break duration curve shows the most significant variation in the OP time, suggesting that the longer the break, the greater the variation in OP performance following it.

This pattern can be explained by the dynamics of fatigue and recovery point. Shorter rest breaks may result in incomplete recovery, which could initially hinder performance, as fatigue accumulates faster than in the case of longer breaks. However, after extended work duration, workers may adapt to shorter breaks by pacing themselves and become more efficient at task execution as they adjust to shorter recovery periods. By contrast, longer rest breaks may allow for higher recovery but potentially result in a steeper decline in performance after extended periods of work owing to overcompensation or loss of momentum.

Additionally, this relationship may reflect the natural variability in individual responses to different rest durations, highlighting the complexity of balancing rest breaks for both recovery and sustained performance. This also suggests that although shorter breaks are less effective for immediate recovery, they may lead to better long-term performance for prolonged tasks.

This OP time behaviour also suggests that there is an optimal window of work after a break, where the performance is best before it starts deteriorating. Moreover, the impact of break duration on performance was not uniform. Longer breaks appeared to cause higher fluctuations in OP performance over time. The optimal post-break period during which workers perform best, is noteworthy, especially in the challenging conditions of cold-storage environments. Bacause, identifying these periods can improve the scheduling of tasks and breaks to maximise efficiency and minimise the health risks associated with extended cold exposure.

To address potential concerns regarding the reliability of the presented results, we examined the possibility that other control variables might also influence the relationship between the time after break and the OP time. Specifically, we introduced the travel distance parameter in Models (6) and (7) to examine their robustness, as summarised in Table 4, because of their relevance to the physical demands of the order pickers. The introduction of travel distance into our analysis showed that it did not significantly alter the cubic relationship of time after the break in Model (6). Similarly, in Model (7), travel distance did not significantly moderate the relationship for any time-after-break variables. Moreover, both models exhibited higher AIC and BIC values than Model (5), indicating that the addition of travel distance did not improve the model fit. Additionally, Models (6) and (7) fit the data less effectively than Model (5), suggesting that although travel distance is an important factor that affects the physical workload in OP, it does not significantly change the established relationship between break duration and OP time in this study.

5. Conclusions

This study investigated the impact of rest breaks on OP performance in a cold-storage warehouse operating at −21 °C. We collected real-world data from a German retailer and analysed 514,953 storage location visits by 40 order pickers using multilevel regression models. A horizontal S-shaped relationship was observed between work time after the break and the OP time, indicating an initial increase in OP time, a plateau, and a subsequent sharp increase. This pattern suggests post-break variability in OP performance at different intervals. Furthermore, we found that the interaction between break duration and work time after a break significantly affected the OP time. Different break durations (15, 30, 45, and 60 min) exhibited different impacts on the OP time, indicating that longer breaks led to more pronounced fluctuations in performance with duration after a break.

Our findings align with previous knowledge on the importance of strategically timed rest breaks for reducing work-related fatigue and enhancing worker performance (Dababneh et al., 2001; Tucker, 2003), revealing that the length of breaks, not just their occurrence, is crucial for improving operational outcomes. The observed horizontal S-shaped

Table 4
Results of a multilevel regression model with interaction effects.

Dependent variable: OP time			
	Model (5) Moderating Effect	Model (6) Robustness 1	Model (7) Robustness 2
Interactions			
Time after break^3 × Break duration	0.000001*** (0.0000001)		0.000001*** (0.0000001)
Time after break^2 × Break duration	−0.000002*** (0.0000004)		−0.000002*** (0.0000004)
Time after break × Break duration	0.000121*** (0.000021)		0.000120*** (0.000021)
Time after break^3 × Travel distance		0.0000001*** (0.00000001)	0.0000001*** (0.00000001)
Time after break^2 × Travel distance		0.0000002** (0.0000001)	0.0000002** (0.0000001)
Time after break × Travel distance		−0.000015*** (0.000006)	−0.000014*** (0.000006)
Moderators			
Time after break^3	−0.0000001 (0.0000001)	0.0000002 (0.00000002)	−0.0000001 (0.0000001)
Time after break^2	0.000017 (0.000012)	−0.000045*** (0.000004)	0.000013 (0.000012)
Time after break	−0.000406 (0.000598)	0.003101*** (0.000225)	−0.000123 (0.000604)
Break duration	−0.001431*** (0.000257)		−0.001411*** (0.000257)
Controls and fixed effects			
Control variables	Included	Included	Included
Fixed effects	Included	Included	Included
Intercept	2.55***	2.51***	2.55***
Observations	514,953	514,953	514,953
AIC	982,822	982,923	983,004
BIC	983,002	983,123	983,249

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

behaviour for the post-break OP time suggests that worker performance changes dynamically throughout the workday. This finding diverges from the linear or exponential OP time assumptions of previous studies and offers a new perspective on how performance deteriorates and recovers in response to work–rest cycles.

These findings have several managerial implications for cold-storage OP operations. First, field studies are key for developing effective and practical work–rest schedules by understanding the resting patterns of workers and the impact of rest breaks on their performance. Given the high variability in break-taking patterns, customising work–rest schedules based on field data is advisable, particularly after identifying the most common break times. Second, the flexibility of the work–rest policy in cold-storage facilities should be leveraged to help workers achieve appropriate rest and optimal post-break performance. Incorporating Bechtold's (1991) categorisation of different types of rest breaks can further enhance the effectiveness of this approach. Third, the variability in the effect of different break durations on OP performance highlights the importance of considering individual differences among workers. Managers could consider implementing more personalised break schedules that cater to each worker's preferences and physical requirements to develop more human-centric warehousing operations. Finally, understanding the horizontal S-shaped relationship between the time after a break and OP performance offers insights into the most productive periods. Managers could use this information to schedule the most labour-intensive tasks during peak performance periods, which typically occur shortly after breaks.

Our findings provide valuable insights that can help policymakers to develop work–rest regulations that improve both worker performance and well-being, particularly in demanding environments like cold storage. The British Frozen Food Federation (2013) recommends that breaks to be taken in heated rest areas, with the timing and length of these breaks tailored according to risk assessments. Factors such as air temperature, wind chills, workload, and protective clothing should be considered in cold work settings. Additionally, Germany's Working Time Act (Bundesministerium der Justiz und für Verbraucherschutz, 1994) mandates at least a 30-min break for shifts exceeding 6 hours. However, high-strain environments such as cold storage often demand more specific rest schedules, which individual companies need to customize to better meet the needs of their workers. Our findings suggest that more flexible, risk-based guidelines would be beneficial—for example, setting worker-specific rather than shift-specific break times across different storage areas within a warehouse operating at various temperatures. By advocating for evidence-based work–rest regulations, this research supports a growing body of knowledge aimed at enhancing worker well-being in human-centred warehousing.

Nevertheless, this study has several limitations that must be acknowledged. Owing to its focus on cold-storage environments, the findings may not be directly applicable to other work environments, such as standard-temperature warehouses. Additionally, the results are based on observational data of rest breaks without interventions involving control over several variables, which requires additional analysis. Moreover, although it acknowledged the variability in workers' break-taking behaviour and preferences, it did not fully analyse the patterns or account for individual differences in physical fitness, health conditions, or previous work experience.

Future research should address these limitations. Additional analyses are necessary to clarify the effects of different environmental conditions, such as temperature and humidity, and a comparison of their effects on the rest-break effectiveness for different OP settings. Additionally, investigating the physiological and psychological factors that contribute to individual variability in resting requirements at different temperatures is necessary. This includes analysing the influence of age, sex, fitness, and health status on recovery rates and post-break performance. Specifically, as discussed in Section 2.3, the experimental data highlighted that the rest-break requirements in cold-storage environments varies with age. However, there is minimal focus on quantifying the optimal development of individualised work–rest schedules. Ranasinghe et al. (2024) highlighted the significant role of organisations in shaping the experiences and expectations of the aging workforce at workplaces. Therefore, implementing policies and practices that support flexible and adaptive rest schedules could lead to a healthier and more productive ageing workforce. Additionally, future research should investigate the influence of individual break-distribution preferences, such as frequency and duration, on worker performance and well-being, and that of potential self-selection bias, where workers choose break times based on individual preferences, on the observed effects. Furthermore, this study primarily emphasised OP performance; therefore, future research should consider a broader perspective by integrating both economic and ergonomic factors, as suggested in frameworks such as that proposed by Grosse et al. (2015). This integrative perspective would allow for a comprehensive assessment of how work–rest cycles influence worker health and well-being, extending the focus to include social sustainability in workplaces.

Moreover, integrating latest technologies, such as wearable devices, could transform how physiological responses are monitored, thereby enhancing health and productivity in cold working environments. These devices could help determine timings for warm breaks and customize break schedules to meet individual needs. Grosse (2024) discussed the use of autonomous sensors to gather real-time feedback from order pickers by using machine-learning algorithms and digital twin models for predictive analytics to facilitate human-centric planning. However, despite the valuable data provided by these advanced sensor systems, they also pose significant ethical and privacy risks if not managed with appropriate level of surveillance and governance. Most importantly, organisations must consider involving workers in decision-making processes regarding the use of their data and the feasibility of decisions to enhance both transparency and trust.

CRediT authorship contribution statement

Thilini Ranasinghe: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dominic Loske:** Writing – review & editing, Validation, Formal analysis, Data curation. **Eric H. Grosse:** Writing – review & editing, Supervision, Resources, Conceptualization.

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Appendix

Table A1
Variance inflation factors and cross-correlation

	VIF	1	2	3	4	5	6
1: Time after Break	1.002	1.00					
2: Break Duration	1.002	0.012	1.00				
3: Travel distance	1.014	0.004	0.011	1.00			
4: Item weight	2.099	−0.001	0.000	−0.040	1.00		
5: Item volume	1.492	0.001	−0.001	0.010	−0.527	1.00	
6: Pick Density	1.468	−0.003	0.002	0.073	−0.527	0.126	1.00

Data availability

The data used for this research are confidential.

References

Baldus, S., Kluth, K., Strasser, H., 2012. Order-picking in deep cold – physiological responses of younger and older females. Part 2: body core temperature and skin surface temperature. Work 41, 3010–3017. https://doi.org/10.3233/WOR-2012-0557-3010.

Bates, D., Maechler, M., Bolker, B., Walker, S., Tanaka, E., 2023. Linear Mixed-Effects Models Using 'Eigen' and S4 (R Package Version 1.1-35.1).

Battini, D., Glock, C.H., Grosse, E.H., Persona, A., Sgarbossa, F., 2016. Human energy expenditure in order picking storage assignment: a bi-objective method. Comput. Ind. Eng. 94, 147–157. https://doi.org/10.1016/j.cie.2016.01.020.

Battini, D., Calzavara, M., Persona, A., Sgarbossa, F., Visentin, V., 2017. Fatigue and recovery: research opportunities in order picking systems. IFAC-PapersOnLine 50 (1), 6882–6887. https://doi.org/10.1016/j.ifacol.2017.08.1211.

Bechtold, S.E., 1991. Optimal work-rest schedules with a set of fixed-duration rest periods. Decis. Sci. J. 22 (1), 157–170. https://doi.org/10.1111/j.1540-5915.1991.tb01268.x.

Bechtold, S.E., Thompson, G.M., 1993. Optimal scheduling of a flexible-duration rest period for a work group. Oper. Res. 41 (6), 1046–1054. https://doi.org/10.1287/opre.41.6.1046.

Bliese, P., Chen, G., Downes, P., Schepker, D., Lang, J., 2022. Multilevel Functions (R Package Version 2.7).

British Frozen Food Federation, 2013. Working in a Cold Store Environment. British Frozen Food Federation. Retrieved from. https://bfff.co.uk/wp-content/uploads/2013/05/Working-in-a-Coldstore-Environment.pdf.

Bundesministerium der Justiz und für Verbraucherschutz, 1994. Arbeitszeitgesetz (ArbZG): Gesetz über die Arbeitszeitgestaltung. Retrieved from. https://www.gesetze-im-internet.de/arbzg/BJNR117100994.html.

Casella, G., Volpi, A., Montanari, R., Tebaldi, L., Bottani, E., 2023. Trends in order picking: a 2007–2022 review of the literature. Product. Manufact. Res. 11 (1), 2191115.

Dababneh, A.J., Swanson, N., Shell, R.L., 2001. Impact of added rest breaks on the productivity and well being of workers. Ergonomics 44 (2), 164–174. https://doi.org/10.1080/00140130121538.

Darwish, M.A., 2023. Optimal workday length considering worker fatigue and employer profit. Comput. Ind. Eng. 179, 109162. https://doi.org/10.1016/j.cie.2023.109162.

De Lombaert, T., Braekers, K., De Koster, R., Ramaekers, K., 2023. In pursuit of humanised order picking planning: methodological review, literature classification and input from practice. Int. J. Prod. Res. 61 (10), 3300–3330. https://doi.org/10.1080/00207543.2022.2079437.

Di Pasquale, V., Fruggiero, F., Iannone, R., Miranda, S., 2017. A model for break scheduling assessment in manufacturing systems. Comput. Ind. Eng. 111, 563–580. https://doi.org/10.1016/j.cie.2017.05.017.

Eilon, S., 1964. On a mechanistic approach to fatigue and rest periods. Int. J. Prod. Res. 3 (4), 327–332. https://doi.org/10.1080/00207546408943065.

Elbert, R., Müller, J.P., 2017. Manoeuvres in manual person-to-parts order picking systems: is there a significant influence on travel time and metabolic rates? IFAC-PapersOnLine 50 (1), 6894–6899. https://doi.org/10.1016/j.ifacol.2017.08.1213.

Fortune Business Insights, 2021. Frozen food market [Online]. Available at: https://www.fortunebusinessinsights.com/frozen-food-market-104138.

Glock, C.H., Grosse, E.H., Kim, T., Neumann, W.P., Sobhani, A., 2019. An integrated cost and worker fatigue evaluation model of a packaging process. Int. J. Prod. Econ. 207, 107–124. https://doi.org/10.1016/j.ijpe.2018.09.022.

Groos, S., Penzkofer, M., Strasser, H., Kluth, K., 2019. Theoretical requirements and real benefit of cold protective clothing for order-pickers in deep cold. In: Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018) Volume II: Safety and Health, Slips, Trips and Falls, vol. 20, pp. 203–212. Springer International Publishing.

Grosse, E.H., Glock, C.H., Jaber, M.Y., Neumann, W.P., 2015. Incorporating human factors in order picking planning models: framework and research opportunities. Int. J. Prod. Res. 53 (3), 695–717. https://doi.org/10.1080/00207543.2014.919424.

Grosse, E.H., Glock, C.H., Neumann, W.P., 2017. Human factors in order picking: a content analysis of the literature. Int. J. Prod. Res. 55 (5), 1260–1276. https://doi.org/10.1080/00207543.2016.1186296.

Grosse, E.H., Sgarbossa, F., Berlin, C., Neumann, W.P., 2023. Human-centric production and logistics system design and management: transitioning from Industry 4.0 to Industry 5.0. Int. J. Prod. Res. 61 (22), 7749–7759. https://doi.org/10.1080/00207543.2023.2246783.

Grosse, E.H., 2024. Application of supportive and substitutive technologies in manual warehouse order picking: a content analysis. Int. J. Prod. Res. 62 (3), 685–704. https://doi.org/10.1080/00207543.2023.2169383.

Hanson, R., Medbo, L., Berlin, C., Hansson, J., 2018. Manual picking from flat and tilted pallet containers. Int. J. Ind. Ergon. 64, 199–212. https://doi.org/10.1016/j.ergon.2017.07.001.

Holmér, I., 1994. Cold stress: Part I—guidelines for the practitioner. Int. J. Ind. Ergon. 14 (1–2), 139–149. https://doi.org/10.1016/0169-8141(94)90011-6.

Holmér, I., Hassi, J., Ikäheimo, T.M., Jaakkola, J.J.K., 2012. Cold stress: effects on performance and health. In: Bingham, E., Cohrssen, B., Powell, C.H. (Eds.), Patty's Toxicology, first ed. Wiley, pp. 1–26. https://doi.org/10.1002/0471435139.tox097.pub2.

Konz, S., 1998. Work/rest: Part II-The scientific basis (knowledge base) for the guide. Int. J. Ind. Ergon. 22 (1–2), 73–99.

Kluth, K., Penzkofer, M., Strasser, H., 2009. Physiological responses of core and skin temperature of two age groups to working in the cold at− 3° C and− 24° C. Occup. Ergon. 8 (4), 147–157. https://doi.org/10.3233/OER-2009-0166.

Kluth, K., Strasser, H., 2008. Physiological responses of heart rate and blood pressure to order-picking in deep cold. Z. Arbeitswiss. (Neue Folge) 62 (4), 239–247.

Kluth, K., Baldus, S., Strasser, H., 2012. Order-picking in deep cold–physiological responses of younger and older females. Part 1: heart rate. Work 41 (Suppl. 1), 3002–3009. https://doi.org/10.3233/WOR-2012-0556-3002.

Kluth, K., Penzkofer, M., Strasser, H., 2013. Age-related physiological responses to working in deep cold. Human Fact. Ergon. Manufact. Serv. Indus. 23 (3), 163–172. https://doi.org/10.1002/hfm.20305.

Morioka, I., Ishii, N., Miyai, N., Yamamoto, H., Minami, Y., Wang, T., Miyashita, K., 2005. An occupational health study on workers exposed to a cold environment in a cold storage warehouse. In: Elsevier Ergonomics Book Series, vol. 3. Elsevier, pp. 199–204.

Morioka, I., Ishii, N., Miyai, N., Miyashita, K., 1998. Effects of work in and outside a cold storage on circulatory functions. Arbete Och Halsa Vetenskaplig Skriftserie 175–177.

Pilcher, J.J., Nadler, E., Busch, C., 2002. Effects of hot and cold temperature exposure on performance: a meta-analytic review. Ergonomics 45 (10), 682–698.

Price, A.D.F., 1990. Calculating relaxation allowances for construction operatives — Part 1: metabolic cost. Appl. Ergon. 21 (4), 311–317. https://doi.org/10.1016/0003-6870(90)90202-9.

Penzkofer, M., Kluth, K., Strasser, H., 2009. Heart rate and work pulses of two age groups associated with working in the cold at$+$ 3° C and$-$ 24° C. Occup. Ergon. 8 (4), 135–145. https://doi.org/10.3233/OER-2009-0165.

Penzkofer, M., Kluth, K., Strasser, H., 2013. Subjectively assessed age-related stress and strain associated with working in the cold. Theor. Issues Ergon. Sci. 14 (3), 290–310. https://doi.org/10.1080/1463922X.2011.617114.

Ranasinghe, T., Grosse, E.H., Glock, C.H., Jaber, M.Y., 2024. Never too late to learn: unlocking the potential of the aging workforce in manufacturing and service industries. Int. J. Prod. Econ., 109193 https://doi.org/10.1016/j.ijpe.2024.109193.

Rijal, A., Bijvank, M., Goel, A., De Koster, R., 2021. Workforce scheduling with order-picking assignments in distribution facilities. Transp. Sci. 55 (3), 725–746. https://doi.org/10.1287/trsc.2020.1029.

Setayesh, A., Grosse, E.H., Glock, C.H., Neumann, W.P., 2022. Determining the source of human-system errors in manual order picking with respect to human factors. Int. J. Prod. Res. 60 (20), 6350–6372. https://doi.org/10.1080/00207543.2021.1991022.

Sgarbossa, F., Vijayakumar, V., 2020. Reducing fatigue level through tasks and breaks assignment in order picking system. In: 21st IFAC World Congress (Virtual) Berlin. Germany.

Tanaka, H., Monahan, K.D., Seals, D.R., 2001. Age-predicted maximal heart rate revisited. J. Am. Coll. Cardiol. 37 (1), 153–156. https://doi.org/10.1016/S0735-1097(00)01054-8.

Tucker, P., 2003. The impact of rest breaks upon accident risk, fatigue and performance: a review. Work. Stress 17 (2), 123–137. https://doi.org/10.1080/0267837031000155949.

Vijayakumar, V., Sgarbossa, F., Neumann, W.P., Sobhani, A., 2022. Framework for incorporating human factors into production and logistics systems. Int. J. Prod. Res. 60 (2), 402–419. https://doi.org/10.1080/00207543.2021.1983225.

Winkelhaus, S., Grosse, E.H., Morana, S., 2021. Towards a conceptualisation of order picking 4.0. Comput. Ind. Eng. 159, 107511. https://doi.org/10.1016/j.cie.2021.107511.

Xu, S., Hall, N.G., 2021. Fatigue, personnel scheduling and operations: review and research opportunities. Eur. J. Oper. Res. 295 (3), 807–822. https://doi.org/10.1016/j.ejor.2021.03.036.

Zhao, X., Liu, N., Zhao, S., Wu, J., Zhang, K., Zhang, R., 2019. Research on the work-rest scheduling in the manual order picking systems to consider human factors. J. Syst. Sci. Syst. Eng. 28 (3), 344–355. https://doi.org/10.1007/s11518-019-5407-y.