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Exploring the performance impact of unit load selection in order picking: evidence from a cold retail supply chain

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Abstract

Purpose – Prior literature has widely established that the design of storage locations impacts order picking task performance. The purpose of this study is to investigate the performance impact of unit loads, e.g. pallets or rolling cages, utilized by pickers to pack products after picking them from storage locations.

Design/methodology/approach – An empirical analysis of archival data on a manual order picking system for deep-freeze products was performed in cooperation with a German brick-and-mortar retailer. The dataset comprises $N = 343{,}259$ storage location visits from 17 order pickers. The analysis was also supported by the development and the results of a batch assignment model that takes unit load selection into account.

Findings – The analysis reveals that unit load selection affects order picking task performance. Standardized rolling cages can decrease processing time by up to 8.42% compared to standardized isolated rolling boxes used in cold retail supply chains. Potential cost savings originating from optimal batch assignment range from 1.03% to 39.29%, depending on batch characteristics.

Originality/value – This study contributes to the literature on factors impacting order picking task performance, considering the characteristics of unit loads where products are packed on after they have been picked from the storage locations. In addition, it provides potential task performance improvements in cold retail supply chains.

Keywords Europe, Warehousing, Retail logistics, Quantitative survey

Paper type Case study

1. Introduction

In the context of order picking as the process of retrieving products from storage locations based on customer orders, it is the backdrop of this paper that it remains a laborious and cost-intensive process of supply chains. This is because it is still widely performed manually,

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especially in the retail context where manual picker-to-parts order picking systems are widely diffused (Boysen *et al.*, 2021). Since order picking accounts for more than 55% of warehouse operation costs (de Koster *et al.*, 2007), it also represents one crucial element for firms to remain competitive (Neumann *et al.*, 2021; Sgarbossa *et al.*, 2020). Optimizing warehouse design elements such as layout design (Roodbergen *et al.*, 2015), storage assignment (Reyes *et al.*, 2019), zoning (de Koster *et al.*, 2012), and routing policies (Masae *et al.*, 2020) is a central avenue through which firms can improve order picking task performance. Recent research showed that the design of storage locations, including height (Loske *et al.*, 2022; Petersen *et al.*, 2005), angle (Calzavara *et al.*, 2017; Hanson *et al.*, 2018), and depth (Hanson and Finnsgård, 2014; Wänström and Medbo, 2008), is particularly effective for improving order picking task performance.

The addressed research problem consists of the fact that the design of the unit loads *where to pick from* at the storage location, including the type and the size, affect order picking task performance, with existing research proving that picking from small plastic containers is faster than picking from EUR-pallets (Neumann and Medbo, 2010). Literature on the design of storage location and unit loads for manual picker-to-parts order picking systems led both scholars and firms to largely conclude that these warehouse design elements reduce the processing time by improving the accessibility of storage locations for pickers, mainly in terms of shape and size. Yet, this research follows the question of the design of another element that might affect order picking task performance; some picking missions require products to be packed (the process of realizing geometric combinations of products assigned to unit loads) after they have been picked from the storage locations. Similar to storage locations, the unit load utilized by pickers to pack products after retrieving them might vary in size and shape. This raises the possibility that the design of the unit load utilized by the pickers to pack products might affect order picking task performance. So far, literature attention has been devoted to the design of the systems where products wait to be picked from, not considering the impact of the unit loads *used to pack on*. In this paper, we want to prove the effect of the design of the unit load used for packing products on processing time, answering the question *"How and to what extent can the design of unit load used for packing products affect processing time in manual picker-to-parts order picking systems?"*. As outlined before, this important step in the order picking process has not yet been analyzed in depth empirically. This is novel and significant, as outlined before, given the overall share of manual order picking cost among all warehouse management cost positions and, in general, with backend handling of retail and many other supply chain processes.

For this purpose, we back this question up by methodologically testing and comparing the impact of two different types of unit load used in retail to pack products (i.e. standardized isolated rolling boxes and standardized rolling cages) on order picking task performance. An empirical analysis of archival data obtained in cooperation with a large German brick-and-mortar (B&M) grocery retailer was conducted to address the question. Our dataset included data from a cold warehouse, including $N = 343{,}259$ storage location visits collected during November 2021. We formulate and apply a parametric log-logistic accelerated failure time model (AFTM) with processing time as the dependent variable, we include the type of unit load used for packing products as an independent variable, and we control for relevant parameters in order picking task performance, e.g. the travel distance, product weight, product, and volume. The model allowed one regression line per order picker, meaning that each regression line shows the correlation between all the selected independent variables and control parameters and the processing time considering the performance of a specific picker. The results of the analysis show that the two types of unit load used for packing products had different regression coefficients for the same picker, meaning that each picker has a specific unit load with which they perform better. Based on these findings, we formulated a batch assignment model to assign picking tasks to workers according to their order picking task performance with the two different unit loads.

The remainder of this paper is structured as follows: Section 2 presents related literature on order picking systems and factors affecting order picking task performance in manual material handling. Section 3 explains our methodology, empirical setting, and data collection. We present the formulation of the log-logistic accelerated failure time model in Section 4. We provide empirical results and analysis in Section 5. The batch assignment model is presented in Sections 6 and 7 draws the conclusion of the study.

2. Related literature

2.1 Order picking systems

Order picking is defined as the process of retrieving products from storage in response to a specific customer request (de Koster *et al.*, 2007). In brick-and-mortar retailing, the basic objective of order picking is breaking up the load units received from suppliers into smaller sets (Dallari *et al.*, 2009). Depending on order characteristics – including order size, assortment, workload variation, load stability, store-specific buildup, product expiry, and lead time – brick-and-mortar retailers may utilize order picking systems with different automation levels, ranging from fully-automated case picking to fully manual picker-to-parts order picking (Boysen *et al.*, 2021).

Automated order picking systems are increasingly applied in distribution centers, since they offer space and time advantages compared to manual systems that makes them particularly fit for e-commerce operations (Azadeh *et al.*, 2019). Recent and detailed reviews about automated order picking systems can be found in Boysen *et al.* (2021)that specifically addressed brick-and-mortar retailing, Boysen *et al.* (2019a, b) and Azadeh *et al.* (2019), demonstrating the increasing interest in exploiting the innovative technologies to introduce warehouse automation (Olsen and Tomlin, 2020). Authors have classified automated order picking systems into two types: (1) automated order picking systems, including cranes/automated forklift (AS/RS), compact storage systems, and conveyors and dispensers, and (2) robot-based order picking systems (Fragapane *et al.*, 2021; Zou *et al.*, 2021). The latter that use free-roaming retrieval robots such as shuttles and AGV, are receiving increasing attention since they offer higher flexibility in managing varying demand requirements (Chen *et al.*, 2022; Löffler *et al.*, 2023). Grocery retailing and especially cold retail, offers an interesting and challenging application for automated order picking systems: for example, refrigerated warehouses could benefit from high-density compact storage systems for saving cooling costs up to 30% (Boysen *et al.*, 2019a, b). These systems could include automatic mobile racks mounted on rails that open an aisle only when accessing a specific SKU is required (Foroughi *et al.*, 2021) that can be served by automatic cranes, automated forklifts, or shuttles (Azadeh *et al.*, 2019). Despite automated picking systems are gaining increasing interest from both research and practice, the very large majority of order-picking activity in warehouses is still performed by human workers (Schiffer *et al.*, 2022) and, in grocery retailing, human involvement remains necessary for most order picking operations (Loske, 2022).

Following Tompkins *et al.* (2010, p. 434), manual picker-to-parts order picking contains the sub-processes of (1) traveling to and from storage locations, (2) searching for storage locations, (3) reaching and bending to access storage locations, (4) physically picking products from a storage location, (5) packing products into orders on a unit load, and (6) documenting picking transactions. In most picker-to-parts order picking systems, human pickers are equipped with industrial trucks when picking stock-keeping units from the picking area on the ground level (de Koster *et al.*, 2007; Gu *et al.*, 2010). The upper shelf levels are utilized as reserve areas where full pallets are stored and manually retrieved to supply the ground level (Boysen *et al.*, 2021).

2.2 Factors affecting picking time in manual material handling

The design of order picking systems is one major component of the warehouse design and includes equipment selection, including rack types, unit load size, or unit load position (Dallari *et al.*, 2009) and operation strategy selection (Gu *et al.*, 2010). Dallari *et al.* (2009) propose a general framework including an input stage (product data, order data, specifications of order picking system structure), a selection stage (specification of equipment and operating strategy, physical and information transformation), and an evaluation stage for the analysis of systems and strategies.

Most of the empirical field-based research on factors impacting order picking task performance in manual material handling is concerned with manual picking and handling tasks in assembly lines. Wänström and Medbo (2008) and Finnsgård and Wänström (2013) are examples of early approaches taking an explorative view on manual material handling processes by testing for a variety of factors. Hanson *et al.* (2016), Calzavara *et al.* (2017), and Hanson *et al.* (2018) are examples of more detailed examinations on the impact of unit load size or unit load position on order picking task performance.

Wänström and Medbo (2008) investigate the impact of materials feeding design on assembly process performance in the context of a workstation in the automotive industry. Their research methods included video recordings, work instructions, and layout drawings. The variables under investigation were the sizes of the packaging types for a storage location, including EUR-pallets, half-size pallets, and two different types of plastic containers. They found that the design of component racks and the choice of packaging types have a major impact on the assembly process performance. Also, Finnsgård and Wänström (2013) explore factors impacting order picking task performance in an automotive assembly line. By conducting 128 full factorial experiments, they found that packaging type, angle of exposure, the height of exposure, and part size have the greatest impact on processing time.

Hanson and Finnsgård (2014) investigated the impact of unit load size on in-plant material supply efficiency for a Swedish automotive assembly industry through empirical field-based research. Their findings indicate that the transition to smaller unit loads resulted in savings for the assembly process as the presentation of the parts was improved. Hanson *et al.* (2016) chose an identical setting but were more concerned with tilting unit loads and the position of products on a unit load. They found considerable differences between the front and the rear sections of the pallet, as well as between the top and the bottom sections, where the picking time varies depending on the position of each component within the container picked from. When opposing order picking from pallets and picking from boxes, Calzavara *et al.* (2017) show that in terms of picking time, picking from a tilted container is beneficial in comparison to picking from a horizontal one. At the same time, picking from a smaller container is beneficial in comparison to picking from a larger one.

Batch assignment generally deals with the question of how existing batches should be assigned to a limited number of pickers (Scholz *et al.*, 2017). Given that batch assignment aims at minimizing the total time required to pick all items in a set of orders, objective functions are designed to minimize travel time, subject to various constraints such as worker capacity, item availability, and order due dates (Boysen *et al.*, 2019; Žulj *et al.*, 2022). Order picker heterogeneity has frequently been taken into account by the batch assignment literature in order to account for individual differences (Matusiak *et al.*, 2017). Srinivas and Yu (2022) propose a collaborative human-robot order-picking system that optimizes order batching, batch assignment and sequencing, and picker-robot routing to minimize the total tardiness of all orders. The study develops an optimization model and a simulated annealing algorithm to handle large instances and shows that the performance of the system is influenced by several factors, including, e.g. human-robot team composition. Rasmi *et al.* (2022) address the optimization of order picking planning in mixed-shelves storage strategy based e-commerce warehouses, which can improve picking efficiency. The proposed decomposition approach effectively balances the trade-off between customer service level and workforce level and provides recommendations for choosing a storage location assignment strategy. Grounded on these approaches, we derive that individual differences of order pickers when packing products into existing orders are underrepresented in the batch assignment literature.

2.3 Synthesis of research streams and research gap

Empirical studies on manual material handling suggest that the size and inclination of unit loads can impact order picking task performance. However, these findings are mostly related to material-feeding processes for in-plant supply and ignore the unit loads used to pack products after picking them from storage locations. Picking products on standardized rolling cages or standardized isolated rolling boxes is common in brick-and-mortar grocery retailing, where picker-to-parts order picking systems are still predominant. Therefore, we identify a research gap for empirical research on unit load selection impacting processing time in manual picker-to-parts order picking systems. We specifically contribute to the literature on packing problems of manual material handling, including, e.g. bin packing, vector packing, vehicle loading, pallet loading, or container loading (Dowsland and Dowsland, 1992). For this purpose, we define *packing* as the process of realizing geometric combinations of products assigned to unit loads (Dyckhoff, 1990).

At the same time, humans are an integral part of manual picker-to-parts order picking systems and need to be integrated (Grosse *et al.*, 2015, 2017). Therefore, it is quite surprising that models investigating the impact of unit load positioning on picking time neglect workforce heterogeneity by assuming the human factor to be static, e.g. Hanson and Finnsgård (2014) and Hanson *et al.* (2018). Calzavara *et al.* (2017) report large variations in picking time between different sections of a pallet and between different heights of boxes. However, the authors miss proposing a methodological integration of human factors for quantitative evaluations. We aspire to close this research gap by including workforce heterogeneity in our econometric model. Additionally, we aspire to formulate a batch assignment method that considers worker heterogeneity. Katiraee *et al.* (2021) underline the importance of the integration of worker heterogeneity for system modeling and design.

3. Empirical setting and data description

The dataset stems from a warehouse for deep-freeze perishable products operated by a large German brick-and-mortar grocery retailer. All zones of the warehouse are operated as picker-to-parts order picking systems with vehicle support provided by industrial trucks. Order pickers supply the storage locations at the ground level with full pallets stored at the reserve area in the upper shelf levels. All products are stored on full pallet units in storage locations for manual picking by order pickers. After the picking, the products are packed on either standardized rolling cages or standardized isolated rolling boxes. The standardized isolated rolling boxes used by the retailer have a net size of 0.735 m in length, 0.825 m in depth, and 1.770 m in height. The standardized rolling cages have a net size of 0.682 m in length, 0.815 m in depth, and 1.850 m in height. Figure 1 illustrates the two types of unit loads utilized in the warehouse under investigation.

Both unit loads are used to pack the entire product range. Grounded on specific characteristics of a grocery store, including, e.g. available store space and backroom capacity, the warehouse management system defines whether standardized isolated rolling containers or standardized rolling cages are utilized for an order. For example, if storage space in a specific store is restricted, the warehouse management systems might try to use more standardized rolling cages as they require less space due to their specific measurement sizes.

Source(s): Authors' own work

Figure 1. Visualization of the unit loads available in the empirical setting

Order picking data from November 2021 is utilized to empirically test the impact of the two different unit loads on order picking task performance. Most warehouse management systems store extensive data on order picking processes which are captured at a very detailed level. Such data has been used to construct a model capable of evaluating the accelerating and decelerating impact of unit load selection on picking time as the dependent variable of interest. We implicitly included in the model workforce heterogeneity through quantitative warehouse management systems data on the past performance of each picker. This implies that the variance and differences in-between different workers regarding their performance levels are included in the analysis.

The initial dataset includes data on batch identification, pick-identification, unit load-identification, article number, number of units picked, length, width, and height of secondary product packaging, volume of secondary product packaging, the weight of the product, and secondary product packaging, timestamps of each pick, the slot address per pick, and the picker-identification. There is a trade-off one needs to consider when defining the units of analysis and the data aggregation level with respect to the process and temporal aggregation level (Gallino *et al.*, 2017). Finer aggregation, e.g. pick level data, has the advantage of higher statistical power as more observations and available variations exist. At the same time, it may be less accurate. Higher aggregation, e.g. batch data or daily picking data, probably hides the impact of order picking system design variables. Considering this trade-off, the study at hand utilizes archival picking data on a pick level. To alleviate any concerns about the validity of the results with respect to alternative decisions on data aggregation, robustness checks are conducted.

The initial dataset includes N = 369,074 storage location visits performed by 26 order pickers. Because real-world archival data is used, the data logs are polluted for several reasons, e.g. personnel breaks or system breakdowns. Thus, all storage location visits lasting longer than 180 s are excluded from this study because they have been identified as non-valid for the underlying scenario. To control for the speed of the industrial trucks, we select storage location visits performed by identical vehicles. Furthermore, a speed ratio is calculated, and all storage location visits with a travel speed higher than 3.33 m/s are excluded. After cross-validating all data cleaning rules with the company, the final dataset comprises N = 343,259 storage location visits performed by 17 order pickers for 2,322 products.

4. Model formulation

Our empirical analysis focuses on estimating the impact of unit load selection for product packing on order picking task performance. Due to the longitudinal nature of our research design, we measure processing time for each order picker repeatedly over time. Because the repetitive measurement of individuals will violate the assumption of independence in linear regression models, we propose an accelerated failure time model with multiple levels, e.g. order pickers. This allows us to measure individual order pickers more than once without artificially inflating our estimates.

To evaluate the impact of unit load selection on order picking task performance in manual picker-to-parts order picking systems, the processing time is chosen as the dependent variable of interest. In order to assess the impact of independent and control variables on the dependent variable, event history analysis, also known as time-to-event analysis or survival analysis, is proposed. Event history analysis summarizes statistical models which are concerned with the probability and the duration until a given event occurs (Mills, 2011). An event is formally defined as the instantaneous transition from the origin state to the destination state (Oud, 2014), reflecting a broad conceptualization transferable to a large scope of scenarios in logistics and supply chain management research. In event history analysis, one essential methodological differentiation relates to the assumption regarding the effect of covariates: While proportional hazard models assume that covariates have a constant impact on the hazard function, the accelerated failure time model assumes an accelerating or decelerating impact (Greene, 2018). In a nutshell, accelerated failure time models are regression models with different likelihood estimators than ordinary least-square regressions and use event time as the dependent variable (Mills, 2011).

This logic is transferred to logistics application scenarios where the impact of independent and control variables on process time is of special interest. The approach is inspired by the landmark paper of Batt and Gallino (2019). In the accelerated failure time model, T represents the time-to-event or survival time which we translate to the general logistics management research context as processing time. T represents a random variable equal to or greater than zero ($T \geq 0$). In parametric survival models, T follows a particular distribution, e.g. exponential, Weibull, logistic, lognormal, or log-logistic. For methodological details, the reader is referred to the comprehensive overview presented by Mills (2011). The choice for the parametric distribution assumed in the accelerated failure time model is made by comparing the model fit for a variety of different distributions through the Log-likelihood ratio (LL).

In the proposed econometric model, the processing time is denoted as T, and it is defined as the elapsed time between the beginning and end of storage location visits performed by one order picker. Because accelerated failure time models are log-linear regression models for T, the basic model is a linear function of the covariate(s) in the form of $Y = \log(T)$ (Mills, 2011). Furthermore, n independent predictor variables (x_n) are defined and their corresponding regression coefficients denoted as β_n. Additionally, ε represents the error term assumed to have a particular parametric distribution.

$$\ln(T) = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + \varepsilon \tag{1}$$

The coefficient in the parametric accelerated failure time model can be interpreted as follows: a positive coefficient indicates that the log processing time increases, leading to longer duration times. A negative coefficient indicates that the log processing time decreases, leading to shorter duration times. The regression coefficients β_n are parametrized by the following transformation (Mills, 2011):

$$100\,(\exp(\beta_n) - 1) \tag{2}$$

The mathematical notation of the econometric model utilized to calculate the estimates is as follows:

$$
\begin{aligned}
\ln(\textit{processing time}) = \beta_0 &+ \beta_1\,\textit{unit load} + \beta_2\textit{travel distance} + \beta_3\,\textit{pick level} \\
&+ \beta_4\,\textit{number of previous picks in the batch} + \beta_5\textit{number of picks} \\
&+ \textit{weight per SKU} + \beta_7\,\textit{volume per SKU} \\
&+ \beta_8\,\textit{primary packages in secondary package} + \beta_9\,\textit{picker experience} \\
&+ \varepsilon
\end{aligned} \tag{3}
$$

where we dummy-code,

$$
\textit{unit load} = \begin{cases} 1 & \textit{if the load unit is a SIRC}, \\ 0 & \textit{otherwise}. \end{cases} \tag{4}
$$

Following the model formulation, we further define the relevant variables and their operationalization.

4.1 Dependent variable

4.1.1 Processing time. This variable operationalizes the time for one unit of order picking task performance. The clock starts when the order picker confirms to start a pick by pushing "next" on a touch display mounted on the industrial truck. The processing time includes picking the product from the storage location and packing it on the unit load. The clock ends after the picker travels to the storage location and picks the product by confirming the pick while pushing a symbol representing the respective unit load on the industrial truck. Both timestamps are used to set the border of the total processing time. Processing time is operationalized as a continuous metric variable and frequently used in logistics management research to evaluate order picking task performance (Batt and Gallino, 2019; Matusiak *et al.*, 2017).

4.2 Independent variable

4.2.1 Unit load. As mentioned in Section 3.1, the warehouse under investigation utilizes two types of unit loads, including standardized isolated rolling boxes and standardized rolling cages. The variable is coded as a binominal dichotomous variable where standardized isolated rolling boxes are coded as 0 and integrated into the reference model. Standardized rolling cages are coded with 1.

4.3 Control variables

4.3.1 Travel distance. Picker traveling is one of the most time-consuming processes in manual picker-to-parts order picking systems (de Koster *et al.*, 2007). Thus, the travel distance from storage location $i-1$ to storage location i in meters is integrated as a continuous variable.

4.3.2 Pick level. In the scenario investigated, each product is stored on an individual pallet and the pallets are stored in one of three possible rack layouts, including, full pallets stored on the ground floor (pick level = 0 meters), half-pallet positioned on the ground floor level of the rack (pick level = 0 meters), and half-pallet positioned on the upper level of the rack at 1.20 m from the floor.

4.3.3 Number of previous picks in the batch. After being grasped from the storage location, products are packed on the unit load. Herein, the filling level is relevant for the processing time. The higher the filling level, the more complicated the packing problem – comparable to the container staffing problem (Dyckhoff, 1990; Dowsland and Dowsland, 1992). The cumulative number of picks per batch is integrated as a discrete variable to control for the packing problem complexity.

4.3.4 Number of picks. One batch includes picks from several storage locations. Herein, multiple picks per storage location may be required, which is quantified as the number of picks and a continuous variable.

4.3.5 Weight per product. The weight of products directly impacts human energy expenditure in manual order picking systems (Battini *et al.*, 2016). Therefore, weight in kilograms is integrated per product as a continuous variable to control for physical effort in manual order picking.

4.3.6 Volume per product. Similar to the weight of products, article dimensions are relevant for the packing process in manual order picking systems. Thus, the volume per product in liters is integrated as a continuous variable to control for the article dimensions impacting the complexity of the packing problem.

4.3.7 Primary packages in secondary package. One secondary package groups a certain number of primary packages to create a product. The number of primary packages in one secondary package is integrated as a continuous variable to control for the design of the product packaging system.

4.3.8 Experience of order picker. Research on learning effects in manual picker-to-parts order picking systems has proven that performance increases through experience (Grosse *et al.*, 2013; Grosse and Glock, 2013, 2015). Therefore, the cumulative picks per order picker identification number and for the entire dataset are included to control for the picker experience. Pickers with less than 1,000 picks are excluded. The experience of the order picker is a discrete variable.

After explaining the dependent, control, and independent variables, relevant descriptive statistics are provided in Table 1. Next, a check for cross-correlation states no significant correlations that would require excluding variables (Mills, 2011). These results are summarized in Table 2.

5. Empirical results and analysis

5.1 General approach

Testing for distribution assumptions of the survival object (i.e. dependent variable processing time) is important before interpreting the estimates in the accelerated failure time model. Therefore, several distributions are tested: Weibull (Model 1), Gaussian (Model 2), logistic (Model 3), lognormal (Model 4), and log-logistic distribution (Model 5).

Table 3 summarizes the results of the accelerated failure time model integrating all control variables and tests for time distribution. The results state that the best model fit with the lowest LL ratio is found in Model (5) with a log-logistic distribution of the dependent variable pick time (LL = 2,550,385). Therefore, a log-logistics accelerated failure time model is applied to the empirical dataset.

5.2 Fixed effects and random effects models

Grounded on the above-stated findings, a fixed-effects log-logistic accelerated failure time model with one regression line fitted to the entire dataset is applied. Therein, the individual order picker is not integrated into the model (Model 6 and Model 7). In contrast, a mixed-effects log-logistic accelerated failure time model allows one regression line per order picker identification number and, therefore, allows an implicit integration of human factors (Model 8 and Model 9). The results indicate that the model fit significantly improves from LL = 2,549,237 (Model 7, fixed-effects model) to LL = 2,530,178 (Model 9, mixed-effects model). At this point, the reader shall be reminded that the lower the LL, the better the model fit. In summary, the best model is a log-logistic accelerated failure time model with mixed

No	Variable	Description of order picking operationalization	Order picking operationalization	Mean	SD
1	Processing time	Timestamps for the begin and the end of the picking process are used to set the border of the total event time	Continuous	16.15	16.86
2	Unit load	The unit load used in the cold storage warehousing might take the form of standardized isolated rolling boxes or standardized rolling cages	Binary dummy 0 = isolated rolling boxes (29.4%) 1 = rolling cages (70.6%)	0.73	0.45
3	Travel distance	The distance in meters from a storage location to a storage location	Continuous	11.81	23.85
4	Pick level	The pick level of the storage location	Binary dummy 0 = ground level (62.77%) 1 = chest level (37.23%)	0.36	0.218
5	Number of previous picks in the batch	One batch consists of several picks. This variable quantifies the position of a pick within the respective batch	Continuous	75.45	57.17
6	Number of picks	Number of picks from one storage location	Continuous	1.26	0.81
7	Weight per product	Weight in kilograms per product, including the products, primary packages, and secondary packages	Continuous	4.49	2.61
8	Volume per product	Volume of the secondary package in liters	Continuous	16.82	12.66
9	Primary packages in the secondary package	Number of primary packages packed into one secondary package representing one product	Continuous	12.31	14.97
10	Experience of order picker	Cumulative number of picks per order picker and in the dataset	Continuous	11,672.41	7,841.50

Note(s): Descriptive statistics for the dataset after the data cleaning process with $N = 343{,}259$ storage location visits, 17 order pickers and 2,322 articles
Source(s): Authors' own work

Table 1. Order picking operationalization of variables and descriptive statistics

effects allowing one regression line per order picker identification number. All relevant results are summarized in Table 4.

When transforming the estimate by applying Equation (2), the results of Model 9 can be interpreted as follows:

(1) *Unit load:* Compared to the reference model calculated for picks with standardized isolated rolling boxes (unit load = 0), the utilization of standardized rolling cages (unit load = 1) reduces processing time by up to 8.42%.

(2) *Travel distance:* Each additional meter of traveling increases pick time by up to 1%.

(3) *Pick level:* Picking from the upper shelf levels rather than from the lower level increases processing time by up to 7.68%. This finding is in contrast with the golden zone assumption for manual order picking systems (Petersen *et al.*, 2005).

Table 2.
Correlation matrix

	Variable	1	2	3	4	5	6	7	8	9	10
1	Processing time	1.00***									
2	Unit load	−0.05***	1.00***								
3	Travel distance	0.04***	0.03***	1.00***							
4	Pick level	0.22***	−0.02***	0.00***	1.00***						
5	Number of previous picks in the batch	0.07***	0.00***	0.00***	−0.02***	1.00***					
6	Number of picks	0.07***	0.00***	0.00***	−0.01***	0.58***	1.00***				
7	Weight per product	0.00***	0.07***	0.02***	−0.06***	0.16***	−0.10***	1.00***			
8	Volume per product	0.16***	0.02***	0.01***	0.00***	0.08***	0.06***	0.10***	1.00***		
9	Primary packages in secondary package	0.00***	0.00***	0.00***	−0.01***	−0.05***	−0.08***	0.10***	−0.03***	1.00***	
10	Experience of order picker	0.09***	0.01***	0.00***	−0.01***	0.43***	0.31***	0.23***	0.22***	0.06***	1.00***

Note(s): ***$p < 0.001$; $N = 343{,}259$ storage location visits included
Source(s): Authors' own work

Table 3. Test for distribution assumption of the dependent variable

Dependent variable: processing time	Model (1) Weibull	Model (2) Gaussian	Model (3) Logistic	Model (4) Log-Normal	Model (5) Log-logistic
Travel distance	0.0079*** (0.0001)	0.1572*** (0.0012)	0.1549*** (0.0009)	0.0116*** (0.0001)	0.0103*** (0.0001)
Pick level	0.0456*** (0.0068)	0.7839*** (0.1283)	0.7265*** (0.0856)	0.1043*** (0.0076)	0.0848*** (0.0068)
Number of previous picks in the batch	−0.0003*** (0.00003)	−0.0046*** (0.0005)	−0.0035*** (0.0004)	−0.0008*** (0.00003)	−0.0006*** (0.00003)
Number of picks	0.1484*** (0.0020)	3.1535*** (0.0350)	2.0863*** (0.0308)	0.1019*** (0.0021)	0.1152*** (0.0021)
Weight per product	0.0139*** (0.0007)	0.2163*** (0.0135)	0.0133 (0.0093)	0.0021** (0.0008)	0.0011*** (0.0007)
Volume per product	0.0031*** (0.0002)	0.0428*** (0.0029)	0.0321*** (0.0020)	0.0029*** (0.0002)	0.0027*** (0.0002)
Primary packages in secondary package	0.0016*** (0.0001)	0.0402*** (0.0021)	0.0174*** (0.0016)	0.0016*** (0.0001)	0.0014*** (0.0001)
Experience of order picker	−0.00001*** (0.000000)	−0.0001*** (0.000004)	−0.0001*** (0.000002)	−0.00001*** (0.000000)	−0.00001*** (0.000000)
Picker fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	2.4490*** (0.0087)	8.9704*** (0.1642)	8.8597*** (0.1124)	2.0487*** (0.0098)	2.1428*** (0.0089)
Observations	343,259	343,259	343,259	343,259	343,259
Log Likelihood	2,558,419	2,883,594	2,717,126	2,566,231	2,550,385
χ^2 (df = 8)	29,811***	29,915***	38,824***	31,904***	33,356***

Note(s): Robust standard errors in parentheses; ***$p < 0.001$
Source(s): Authors' own work

Table 4. Results of the fixed effects and mixed effects model

Dependent variable: processing time	Model (6) Fixed effects model	Model (7) Fixed effects model	Model (8) Mixed effects model	Model (9) Mixed effects model
Unit load		-0.1130^{***} (0.0033)		-0.0842^{***} (0.0031)
Travel distance	0.0103^{***} (0.0001)	0.0103^{***} (0.0001)	0.0100^{***} (0.0001)	0.0100^{***} (0.0001)
Pick level	0.0848^{***} (0.0068)	0.0839^{***} (0.0068)	0.0775^{***} (0.0064)	0.0768^{***} (0.0064)
Number of previous picks in the batch	-0.0006^{***} (0.00003)	-0.0005^{***} (0.00003)	-0.0004^{***} (0.00003)	-0.0004^{***} (0.00003)
Number of picks	0.1152^{***} (0.0021)	0.1163^{***} (0.0021)	0.1101^{***} (0.0020)	0.1110^{***} (0.0020)
Weight per product	0.0011^{***} (0.0007)	0.0009^{***} (0.0007)	0.0006^{***} (0.0007)	0.0004^{***} (0.0007)
Volume per product	0.0027^{***} (0.0002)	0.0026^{***} (0.0002)	0.0022^{***} (0.0002)	0.0021^{***} (0.0002)
Primary packages in secondary package	0.0014^{***} (0.0001)	0.0014^{***} (0.0001)	0.0013^{***} (0.0001)	0.0013^{***} (0.0001)
Experience of order picker	-0.00001^{***} (0.000000)	-0.00001^{***} (0.000000)	-0.000005^{***} (0.000000)	-0.000005^{***} (0.000000)
Picker fixed effect	No	No	Yes	Yes
Constant	2.1428^{***} (0.0089)	2.2212^{***} (0.0091)	2.1540^{***} (0.0083)	2.2109^{***} (0.0086)
Observations	343,259	343,259	343,259	343,259
Log Likelihood	2,550,385	2,549,237	2,530,933	2,530,178
χ^2	$33{,}356^{***}$ (df = 8)	$34{,}504^{***}$ (df = 9)	$34{,}370^{***}$ (df = 8)	$35{,}125^{***}$ (df = 9)

Note(s): Robust standard errors in parentheses; $^{***}p < 0.001$
Source(s): Authors' own work

(4) *Number of previous picks in the batch:* Each additional pick per batch increases processing time by up 0.04%.

(5) *Number of picks:* Each additional product to pick increases processing time by up 11.10%.

(6) *Weight per product:* Each additional kilogram to pick increases processing time by up to 0.04%.

(7) *Volume per product:* Each additional liter to pick increases processing time by up to 0.21%.

(8) *Primary packages in a secondary package:* Each additional package in the product increases processing time by up to 0.13%.

(9) *Experience of order picker:* every 1,000 cumulative picks decreases processing time up to 0.50%.

5.3 Robustness checks

To alleviate any concerns about correlated residuals or picker-specific effects, two robustness checks are conducted. This includes a 50 vs 50% sample split through random numbering and a model with random picker selection in Table 5. For all robustness checks, the estimates of the independent variables of interest remain mostly constant. Thus, the results are robust to picker-specific effects.

6. Unit load assignment incorporating pickers heterogeneity

The results of the log-logistic accelerated failure Model (9) proved that picking from rollable containers or from roll cage loads has different performance on the pick time. Therefore, an optimization model is proposed to decide whether a batch needs to be packed into a box or a roll cage. This optimization matches the characteristics of the unit load with specific and individual human factors like height or age while assigning batches to pickers. This problem called the linear sum assignment problem (Burkard *et al.*, 2012), is a special case of a linear programming problem (Cattrysse and van Wassenhove, 1992), and is one of the fundamental combinational optimization problems in the branch of operations research. The goal is to minimize the total assignment costs z (Lawler, 1963). Therein, m batches need to be assigned to n workers ($n \geq m$) in such a way that each batch is assigned to one worker, while each worker has no more than one batch assigned. Formally, in an assignment problem, the number of batches equals the number of workers. When this property is not fulfilled, it is possible (in polynomial time) to insert dummy batches and manipulate the problem to have a proper problem (Burkard *et al.*, 2012).

Assuming $n = m$, the basic description of the assignment problem is as follows:

$$\min z = \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} y_{ij} \tag{5}$$

s.t.

$$\sum_{i=1}^{n} y_{ij} = 1 \;\; for\, j = 1, 2, \ldots .n \; (each\, job\, is\, assigned\, to\, one\, worker)$$

$$\sum_{j=1}^{n} y_{ij} = 1 \;\; for\, i = 1, 2, \ldots .n \; (each\, worker\, has\, one\, job\, assigned)$$

Table 5. Robustness checks for log-logistic accelerated failure time model

Dependent variable: processing time	50/50 sample split for model (7) Fixed effects	Random picker for model (9) Fixed effects	50/50 sample split for model (7) Mixed effects	Random picker for model (9) Mixed effects
Unit load	−0.1019*** (0.0047)	−0.1373*** (0.0046)	−0.0761*** (0.0043)	−0.0976*** (0.0043)
Travel distance	0.0103*** (0.0001)	0.0101*** (0.0001)	0.0100*** (0.0001)	0.0099*** (0.0001)
Pick level	0.0864*** (0.0096)	0.0649*** (0.0096)	0.0780*** (0.0090)	0.0593*** (0.0092)
Number of previous picks in the batch	−0.0006*** (0.00004)	−0.0006*** (0.00004)	−0.0004*** (0.00004)	−0.0005*** (0.00004
Number of picks	0.1158*** (0.0029)	0.1060*** (0.0028)	0.1107*** (0.0028)	0.1041*** (0.0027)
Weight per product	−0.0001*** (0.0010)	−0.0038*** (0.0010)	−0.0001*** (0.0010)	−0.0031*** (0.0010)
Volume per product	0.0024*** (0.0002)	0.0023*** (0.0002)	0.0024*** (0.0002)	0.0020*** (0.0002)
Primary packages in secondary package	0.0012*** (0.0002)	0.0016*** (0.0002)	0.0011*** (0.0002)	0.0016*** (0.0002)
Experience of order picker	−0.00001*** (0.000000)	−0.00002*** (0.000001)	−0.000005*** (0.000000)	−0.00001*** (0.000001)
Constant	2.2098*** (0.0128)	2.3413*** (0.0128)	2.2027*** (0.0120)	2.3071*** (0.0123)
Observations	171,866	170,928	171,866	170,928
Log Likelihood	2,539,824	2,549,237	2,531,730	2,530,178
χ^2	17,385.1700*** (df = 9)	16,718.9900*** (df = 9)	17,731.1700*** (df = 9)	16,600.3400*** (df = 9)

Note(s): Robust standard errors in parentheses; ***$p < 0.001$
Source(s): Authors' own work

$$y_{ij} = \begin{cases} 1, \textit{if the worker i is assigned to job j} \\ 0, \textit{if the worker i is not assignes to job j} \end{cases}$$

where,

n number of workers and batches ($i = 1, \ldots, n$)

$c_{i,j}$ unit cost of assigning worker i to batch j ($i = 1, \ldots, n; j = 1, \ldots, n$). It will be explained in the remainder of the section how these costs are obtained.

$y_{i,j}$ worker i assigned to batch j (1 if assigned, 0 otherwise)

Once the model is solved, dummy batch assignments are identified and a subset of the workers will not be used. Grounded on this general linear model above, which can be solved very efficiently in polynomial time, the integration of individual worker characteristics is proposed. These individual characteristics are quantified through the AFTM analysis introduced in the previous chapters, and also take into account which unit load is used by each order picker during the shift under investigation. This includes an order picking operationalization through the individual intercepts of each worker i, which is denoted as b_{0i}. Furthermore, the random slope allows individual regression weights for a given number of beta-coefficients, denoted as b_{1i}, e.g. the coefficient for picking containers and the ability of a picker to process containers faster than other pickers do. The regression weights are multiplied by the individual batch characteristics. Herein, x_{1i} sets the characteristics of the batch n, e.g. whether a batch needs to be packed into rollable containers or a roll cage. Figure 2 visualizes our procedure and highlights the mapping between the coefficient b describing the characteristics of workers, the coefficient x describing the characteristics of the batches, and the costs c of the assignment problem.

In a nutshell, the optimization model allows to assign batches where products need to be packed into standardized isolated rolling boxes to pickers that are good at packing these units. The same applied to the standardized rolling cages. Note that the model assumes that each worker is assigned to one batch and vice versa.

The batch assignment model considering worker heterogeneity is then applied to the real-world dataset, where 343,259 storage location visits are aggregated to 136 batches according to the existing batch-IDs. These batches represent the batches in the optimization model and are assigned to 17 order pickers representing the workers. The results indicate that processing times can be reduced with respect to the explained assignment model by about 20% on average when assigning batches to pickers by taking worker heterogeneity into account. Figure 3 illustrates the distribution of the potential cost savings in categories from below 10% to nearly 40%.

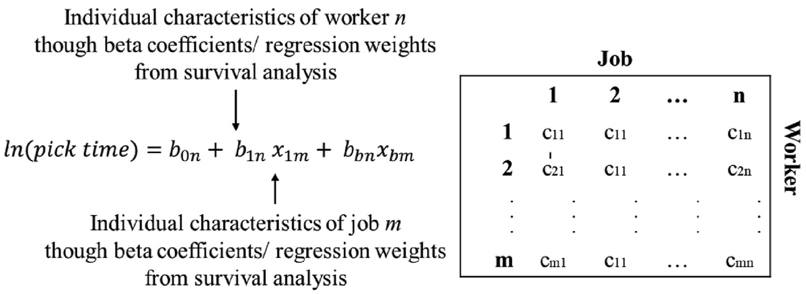
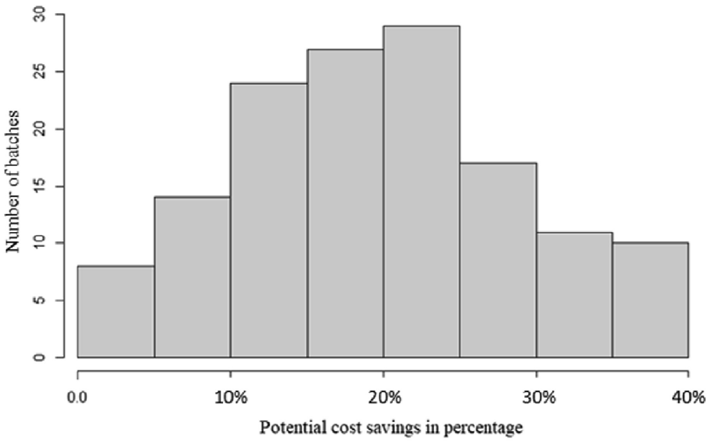


Figure 2.
Visualization of procedure for batch assignment based on individuals

Source(s): Authors' own work



Source(s): Authors' own work

Figure 3.
Potential cost savings through human-centered batch assignment

7. Conclusion

The aim of this study was to answer the research guiding question, *"How and to what extent can the design of unit load used for packing products affect processing time in manual picker-to-parts order picking systems?"*. Therefore, a log-logistic accelerated failure time model was applied to a unique empirical dataset comprising $N = 343{,}259$ storage locations by 17 order pickers in cold storage warehousing during November 2021.

The findings of this study provide quantitative evidence that compared to standardized isolated rolling boxes, the utilization of standardized rolling cages can decrease processing time by up to 8.42% and, in this way, improve order picking task performance. Therefore, this is empirical proof that specified unit load selection can significantly impact processing time as an economic outcome variable of order picking systems.

From a theoretical perspective, the findings of this study contribute to the stream of literature investigating factors impacting order picking task performance. The characteristics of unit loads where products are packed after they have been retrieved from the storage locations have not generally been considered by existing research. Therefore, we argue that this study investigated a second crucial element of the order picking task performance process, especially in cold retail supply chains – not where to pick from, but where to pack on. Furthermore, our findings can enhance the utility of optimization and analytical models used in supply chain management. By incorporating our quantitative insights on unit load selection as an additional constraint, these models can provide more accurate and comprehensive decision support, influencing areas such as batch assignment, batch configuration, and performance forecasts.

This can be further extended towards the human factor and heterogeneity angle in operations management: If the batch allocation is applied in relation to identified human-specific variances in performance in relation to unit load selection, this could be a major improvement. The applied simulation study in this regard states that, on average, close to 20% and even up to 40% of pick time can be saved this way.

From a managerial perspective, the findings span an interesting trade-off between food supply chains and brick-and-mortar grocery retailing. The empirical results indicate that standardized rolling cages accelerate processing time and, therefore, possibly lead to a reduction of personnel costs with the ceteris paribus assumption of a fixed order volume. However, when designing the distribution channels of standardized rolling cages to supermarket stores, deep-freeze transports are necessary. In light of rising energy costs in the context of the Ukrainian crisis, as well as sustainability issues (Hoang *et al.*, 2023; Klumpp, 2018; Rivera-Valle and Silva, 2023), deep freeze transport logistics may cause subsequent costs. Therefore, logistics managers can ground a supply chain cost analysis on the empirical findings of this study. Management is then using the applied calculation models and values for their own cost and process planning in their specific process setting. Furthermore, store-specific characteristics defining unit load selection are well-established in retail practice. Our findings can, however, make an important contribution to quantifying how positive effects could look when changing this. When retail managers decide to change backroom cooling capacity in order to enable large-scale use of non-isolated but smaller rolling cages, our empirical results can contribute to return-on-investment calculations.

This study has several limitations, which provide space for further research avenues. These may include but are not limited to (1) A triple-bottom-line sustainability evaluation approach for the impact of unit load selection in brick-and-mortar grocery retailing. This is especially the case for cold supply chains where transport temperature becomes relevant. (2) A multi-echelon supply chain evaluation integrating transport and in-store logistics perspectives. This is especially the case for in-store operations where limited cooling capacities of grocery stores may require a certain unit load, e.g. standardized isolated rolling boxes. (3) Finally, a simulation study addressing the potential economic advantages using the acceleration and deceleration estimators may spawn interesting insights for logistic scholars and practitioners. Given the fact that conditions in retail supply chains are frequently and rapidly changing nowadays, logistics managers need to design efficient, sustainable, and resilient food supply chains–more than ever before.

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