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Storage systems' impact on order picking time: An empirical economic analysis of flow-rack storage systems

1. Introduction

Within the field of warehouse engineering and management, order picking (OP) is a labor-intensive activity that accounts for approximately 55% of warehouse operating costs (Giannikas et al., 2017). Due to its economic importance, OP has become a focal point for a large number of retail managers and researchers (Boysen et al., 2021). Despite the increasing availability of automation technology in the market, many warehouses still rely on human workers to perform OP activities (Lombaert et al., 2022). Warehouse managers face various challenges today, including the handling of volatile orders, the hiring and maintenance of a qualified and motivated workforce, and the provision of workplaces that do not expose the workforce to unnecessary injury risks.

To improve workers' well-being, it is necessary to consider mental, physical, and psychological factors in the design of the work system (Grosse et al., 2017; Vijayakumar et al., 2021). One aspect that system designers have to account for in this context is worker heterogeneity (e.g., differences in skills or experience), which may impact both worker well-being and worker performance (in the case of picking, OP time [Hoberg et al., 2020; Matusiak et al., 2017]).

More than a decade ago, Dallari et al. (2009) emphasized that empirical evidence on the interaction of order pickers with storage systems is largely missing. We will show in the literature review in Section 2 that this is still the case today, particularly for flow-rack storage systems. This paper addresses this research gap and reports the results of a field study that compared the performance of a flow-rack storage system to that of a normal pallet rack storage system. The study pays special attention to the impact of individual worker heterogeneity on OP system performance.

We formulate two research questions addressing the interface between engineering (storage system design) and management (OP time) when implementing flow-rack systems. With our first research question (RQ), we intend to analyze how system design influences OP time: RQ_1 – *How does the use of flow-rack storage systems influence OP time?* The second question addresses the role of picker heterogeneity in the picking process: RQ_2 – *How does order picker heterogeneity influence the model fit measuring the relative performance of flow-rack storage systems?*

These questions are addressed in an empirical analysis of archival data obtained in cooperation with a large German brick-and-mortar (B&M) grocery retailer. The warehouse under investigation applies two storage systems: a full-pallet storage system and a high-density flow-rack storage system. The company decided to use both types of systems due to the slow-moving and fast-moving stock keeping unit (SKU) types within the same assortment.

Our dataset includes a total of 2,357,976 picks performed by 192 order pickers in 2021. We formulate and apply a parametric log-logistic accelerated failure time model (AFTM) with OP time as the dependent variable (DV). To answer RQ_1, we include the storage system as an independent variable (IV) and control for relevant parameters in OP (e.g., the travel distance, weight and volume per SKU, or the number of picks retrieved from the respective storage system). For RQ_2, we formulate a mixed-effects model allowing one regression line per order picker and compare the model fit with the fixed effects model, assuming no worker heterogeneity.

Our study is an effort to gain empirical insights into the impact of different storage systems on OP time in light of individual worker heterogeneity. We aspire to contribute to the extant literature as follows: Gue et al. (2006) built analytical and simulation models to evaluate storage systems with high space utilization, similar to the high-density flow-rack storage system in our study. Their work provides insights into the effect of pick density on operator blocking. Our study extends the work of Gue et al. (2006) by empirically examining how flow-rack storage systems perform in terms of OP time compared to pallet rack storage systems. Furthermore, we explicitly include individual worker heterogeneity in our mixed-effects log-logistic AFTM—an aspect that was ignored in the work of Gue et al. (2006). Battini et al. (2018) proposed a storage assignment method that considers the trade-off when storing and picking from pallet rack storage systems compared to flow-rack storage systems. We extend this work with an empirical assessment of OP and replenishing tasks, which could subsequently be used for conceptual, analytical, and simulation models.

The remainder of this paper is structured as follows: In Section 2, we present a brief literature review. After explaining the applied methodology in Section 3, we present the empirical setting in Section 4. Section 5 provides the analysis results, and Section 6 discusses the relevant implications and extensions. We further detail the implications for theory and practice and present further research avenues in Section 7.

2. Literature review

2.1. Warehouse system design

Warehouse and OP system design has been a popular area in engineering and management research for decades (de Koster et al., 2007). The fit of a warehouse system to a specific industry application mainly depends on the system's order characteristics (Richards, 2021). While e-commerce retailers face low-volume, high-mix orders, B&M retailers face high-volume, low-mix orders when processing orders from grocery stores (Boysen et al., 2021).

B&M grocery retailers process large orders with medium assortment sizes and face seasonal peaks with highly volatile workloads (Hübner et al., 2015). Warehouse operations in B&M grocery retailing include, for example, receiving, storing, OP, sorting, cross-docking, and shipping SKUs, where manual OP is considered the most cost- and time-intensive process (Richards, 2021). In practice, manual OP is often operated with vehicle support by industrial trucks, where human order pickers visit picking locations in a sequence defined by a pick list to retrieve an SKU from these locations (Dallari et al., 2009). Forklift operators keep the ground level supplied with SKUs by retrieving full pallets from the reserve area and replenishing picking locations (Tompkins et al., 2010).

Most retailers design manual warehouse systems that can easily be adapted to varying workloads. Gu et al. (2010) categorized five major warehouse system design problems: the design of the overall structure with functional departments, warehouse size and dimensions, the design of the department layout, equipment selection, and the definition of the operation strategy. Decisions on the warehouse structure, dimensions, layout, and operation strategy (e.g., OP strategy) are—for the most part—driven by economic objectives that take into account investment and operating costs. In contrast, equipment selection is located at the interface of engineering and management.

In summary, we contribute to the research on equipment selection in warehousing at the interface of engineering and management by evaluating the impact of flow-rack storage system design on the performance of manual OP systems.

2.2. Storage system design

Equipment selection in OP systems, in general, includes decisions on material handling and storage system design. While material-handling systems—and especially technical support by assistive devices—are a well-examined research domain (Battini et al., 2015; Glock et al., 2021), only a few works have evaluated alternative storage systems. The focus of these works was on the comparison of different pallet storage systems.

One of the early works in this area was by White et al. (1981), who proposed analytical models to compare block-stacking, as well as single-deep and double-deep pallet racks. Calzavara et al. (2019) compared full-pallet and half-pallet single-deep storage systems in terms of cost, workload, and body postures order pickers need to adopt and found that both rack designs can be beneficial for alternative applications and SKU characteristics. Calzavara et al. (2017) proposed economic and ergonomic performance measures for storage systems in which orders are picked from full pallets, half pallets, and half pallets equipped with a pull-out system. From an economic perspective, Calzavara et al. (2017) found that a half-pallet storage system is suited for an SKU picked a couple of times per month, while full pallets are recommended for an SKU picked with a higher frequency to reduce pallet replenishments. From an ergonomic perspective, storage on pallets is the most suitable solution when the SKU weight is high. For light SKUs, half pallets are suggested with high quantities per pick on the lower rack and low quantities per pick on the higher rack.

In addition to pallet storage, other works deal with the evaluation of different storage systems. Gue et al. (2006), for example, built analytical and simulation models to evaluate storage systems with high space utilization. They paid special attention to picker blocking and found that when the OP system is busier and pick density is high, congestion is less of a problem, and workers are more productive. The potential impact of different storage systems on pick time was studied by Finnsgård and Wänström (2013), who conducted an experimental study in an automotive assembly line setting. Their results showed that packaging type, angle of exposure, height of exposure, and part size had a higher impact on manual picking time than other factors. The height of exposure refers to the height of the storage location and, therefore, the storage system design. Picking from a height between the picker's waist and shoulders (which is frequently referred to as the "golden zone"; see Petersen et al. [2005]) is considered economical and ergonomically efficient.

Research, particularly on flow-rack storage systems, is scarce. One notable exception is the work of Battini et al. (2018), who proposed a storage assignment method for pallet-rack and flow-rack storage systems and considered both restocking and picking activities. The method considers total pallet refill time, total carton refill time, total picking time, and total travel time, among others. Applying this method to an industrial case with a B&M retailer, they found that 3,355 out of 7,683 SKUs should be stored in high-density flow-rack storage systems rather than full-pallet storage systems.

In summary, our literature review has shown that high-density flow-rack systems have not received much attention in prior research. However, warehouse system design elements, such as flow-rack systems, are strategic in nature and particularly important, as they affect the design of operation strategies in manual OP systems and the overall warehouse and intralogistic setup (Baker & Canessa, 2009).

2.3. Human factors and worker heterogeneity in manual OP

Matusiak et al. (2017) proposed a multilevel model to account for order-picker heterogeneity. The integration of random intercepts allowed for one regression line for each individual observed in their dataset (Matusiak et al., 2017). This significantly improves their model fit because worker heterogeneity is methodologically considered.

In addition to equipment and storage systems, human workers and their individual characteristics also influence the performance of manual OP systems (Glock et al., 2017).

Considering human factors in planning OP activities is therefore central to long-term business success (Grosse et al., 2015), as it triggers a more realistic planning outcome that takes into account the individual requirements of human workers. This enhances economic performance, quality, human well-being, and workplace satisfaction (Grosse et al., 2017).

Although research that considers human factors in OP is still limited, publication numbers have increased recently in this field (for recent reviews, see Vanheusden et al. [2022] and de Lombaert et al. [2022]). Related works focused on physical human factors and investigated, for example, how pallets should be rotated in an OP warehouse to reduce both the workers' load on the lower back and picking time, considering different working postures and SKU weight (Glock et al., 2019). Other studies have analyzed how SKUs should be assigned to different rack systems to reduce both costs and human energy expenditure (Calzavara et al., 2017; Calzavara et al., 2019). Diefenbach and Glock (2019) also considered the energy expenditure needed for picking SKUs with different weights and body postures and developed a mixed-integer program with different objective functions (minimizing either total walking distances or total ergonomic strains) to design a U-shaped OP area. They found that both objectives were only marginally conflicting.

Despite physical labor, OP also requires cognitive effort, for example, in searching for SKUs or remembering storage locations (Grosse & Glock, 2015). This makes the work experience of the individual order picker a determinant of OP performance, as task times in OP are not constant but are subject to individual learning and worker skills (Sgarbossa et al., 2022). Human learning, which leads to performance improvements in completing a manual task due to repetition and increasing practice and experience, has been well studied in the operations management literature, although works that employ empirical data are still rare (Glock et al., 2019). With regard to OP, a few experimental studies have shown that learning effects occur and that the individual learning progress of workers affects OP performance in terms of OP time and pick errors. The first work in this area is that of Grosse and Glock (2013); it evaluates field data on the performance of inexperienced order pickers in a warehouse of a household products manufacturer. Well-known learning curves were fitted to the data to illustrate individual performance and quality improvement. A similar approach based on curve fitting was presented by Stinson (2014), who compared the performance of temporary workers to that of experienced order pickers.

While both studies confirm that learning effects occur in OP and that experienced workers reach a learning plateau at some point, some variance in performance cannot be explained based on experience alone and could be caused by individual skills or work pressure. In a laboratory setting, Winkelhaus et al. (2018) observed that physical and mental fatigue can negatively impact worker learning. Another study analyzed empirical data from an online women’s apparel retailer (Batt & Gallino, 2019). They studied how worker experience and SKU characteristics impact OP time, particularly searching for SKUs (Batt & Gallino, 2019). They developed a simulation model with the objective of minimizing expected pick time rather than travel distance. The results imply that pick times can be improved by incorporating pick density per storage location and learning/experience into the order picker routing problem.

Other studies have considered worker learning in OP planning models to improve the models’ validity for OP practice. Grosse et al. (2013) studied storage reassignment decisions and showed that too frequent changes in storage assignments led to losses in worker experience and performance. Grosse and Glock (2015) developed a planning model that can be used to assign workers to specific warehouse zones in a way that utilizes their individual learning characteristics as well as possible. Zhang et al. (2019) integrated worker learning into an order-batching model and showed how this can improve the accuracy and predictability of planning outcomes. They concluded that improving order pickers' learning abilities through training is beneficial (Zhang et al., 2019). Also related to order batching, Matusiak et al. (2017) used joint order batching and generalized assignment model to assign the right picker to the right order batch based on his/her individual skills. Taking this worker heterogeneity into account, they were able to reduce OP time by up to 10% (Matusiak et al., 2017). In summary, considering human factors and worker heterogeneity is crucial for developing realistic OP planning models and deriving valuable managerial conclusions.

2.4. Summary and contribution

Although storage system design is highly relevant for OP system performance (Finnsgård & Wänström, 2013), the evaluation of different storage systems has received little attention in the academic literature. Our main contribution lies in providing empirical evidence on how alternative storage systems influence OP performance and in incorporating individual order picker heterogeneity into our economic assessment of a flow-rack storage system—similar to the multilevel model applied by Matusiak et al. (2017).

The extant literature has also established the impact of order picker characteristics, such as order picker experience (Batt & Gallino, 2019; Loske, 2022), the picking level height (Finnsgård & Wänström, 2013), and workload (Kudelska & Pawłowski, 2020), on OP time. However, most of these studies examined the constructs in isolation with direct cause–effect relationships. Our work goes beyond these earlier contributions and investigates the moderating effect of storage systems on, for example, the impact of order picker experience on OP time. In summary, our objective is to quantify the impact of two alternative storage systems—high-density flow-rack storage systems versus full-pallet rack systems—on OP time using empirical data.

3. Case study

3.1. Description

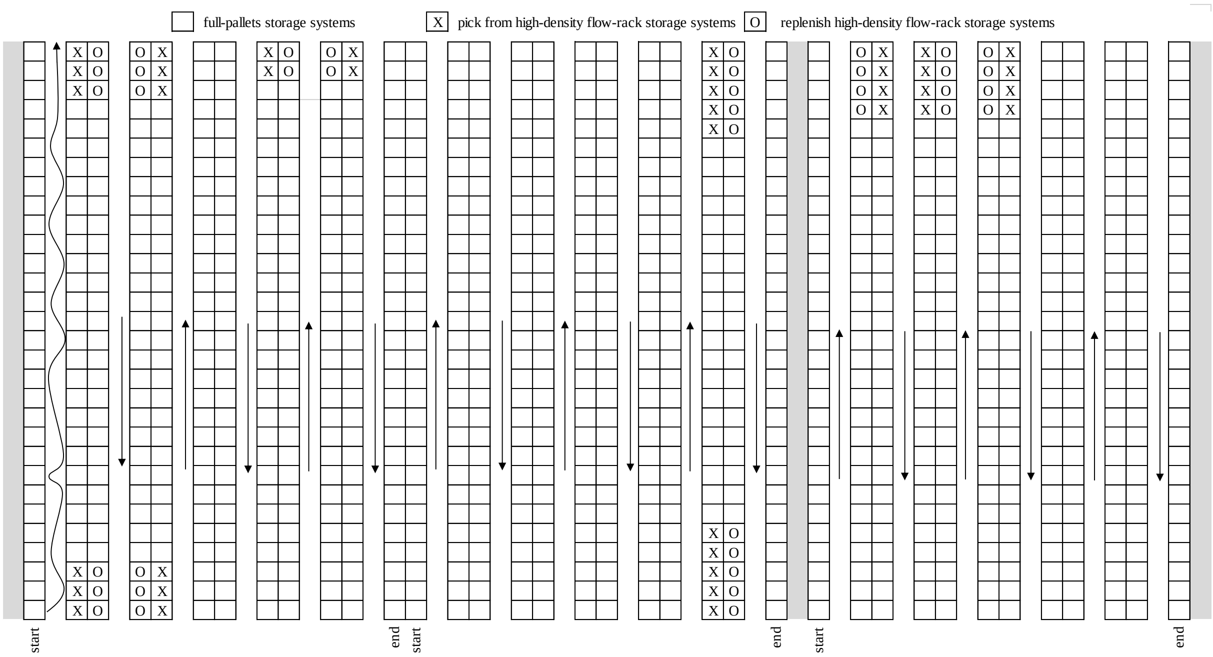
A case study was carried out in cooperation with a B&M grocery retailer operating several warehouses in Germany. The warehouse under investigation stores perishable, non-cooled SKUs in 36 aisles and 6,098 pick locations. Two separate storage areas are present in the same warehouse, storing an identical assortment due to historical capacity extensions. The differentiation of slow-moving and fast-moving SKUs within the same assortment was pivotal for the company when deciding to implement different storage systems. Slow-moving SKUs are placed in flow racks to save space, whereas fast-moving products are placed on pallets to allow for larger storage quantities.

We take advantage of the rack layouts to identify the impact of storage systems on OP time. The key benefits of the underlying systems and dataset for our analysis are as follows: (1) SKUs assigned to one batch are picked sequentially by a single order picker without intermediate tasks, (2) volume and weight measures for each SKU are collected upon arrival at the warehouse, and (3) the rack layouts are well suited to control for the height of the storage location, as the levels are fixed and standardized within the entire warehouse. In summary, the data allow us to directly observe the location and time of each shipment and pick and to utilize this information for calculating retrieval and stack height, travel distance, and time between picks.

In the first storage system, SKUs are retrieved from full pallets stored on the floor level (referred to as full-pallet storage systems). In the second storage system, SKUs are retrieved from a flow-rack system that stores 20 different SKUs on the ground floor on an area corresponding to the size of three pallets (referred to as high-density flow-rack storage systems). While 5,034 pick locations are part of full-pallet storage systems, 1,064 pick locations are assigned to high-density flow-rack storage systems. Herein, one SKU bundles several items and is assigned to exactly one storage location. Each storage location has one unique identification number and stores exactly one SKU.

To replenish the pick locations, human operators equipped with manually steered forklifts perform storage and retrieval operations. Figure 1 illustrates the layout of the specific warehouse under examination, where the picker is routed, as depicted by arrows in a z-pick pattern or z-shape (Hsieh & Tsai, 2006). In this figure, we see the first picker route on the left side of the first aisle, traveling from bottom to top and indicating the typologies of storage systems along the way (see explanations in Figure 1).

Figure 1. Warehouse layout in the examined case study



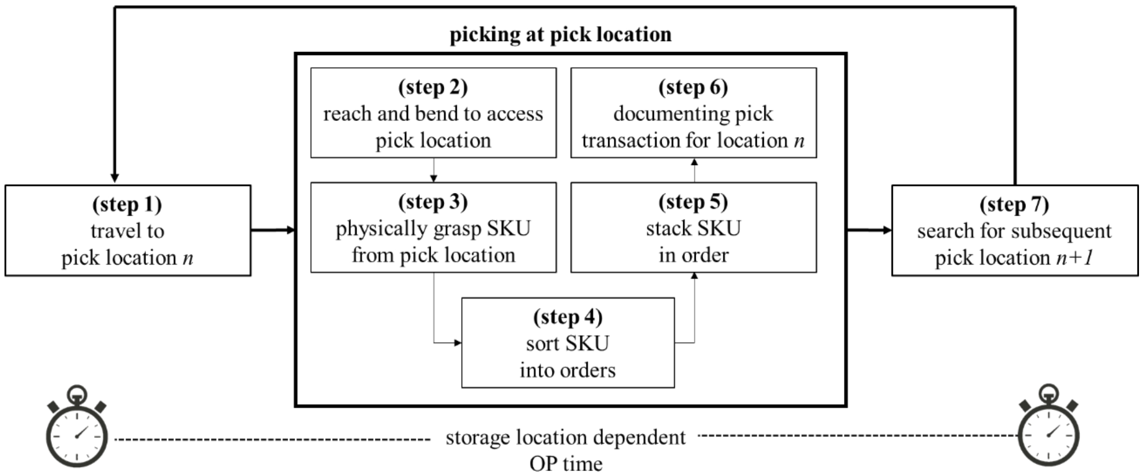
The high-density flow-racks have four different levels, as illustrated in **Figure 2**, and all shelf lines of the high-density flow-rack storage systems are colored according to the pick level and in line with a visual representation of the personal digital assistant utilized by the pickers. The racks have a ground floor level (green), Level 1 (blue) is at 0.60 meters from the floor, Level 2 (yellow) is at 1.20 meters from the floor, and Level 3 (red) is at 1.80 meters from the floor, as can be seen in Figure 2 in the corresponding real-life warehouse setting.

Figure 2. Sample front view of the high-density flow-rack storage system

The OP process examined in the case study involves picking SKUs nested in batches according to the following steps (see Figure 3): (step 1) travel to pick location *n* with a manually steered industrial truck, (step 2) reach and bend (body posture depends on the rack layout) to access pick location *n*, (step 3) physically pick up or grasp the required quantity of the SKU from pick location *n*, (step 4) sort SKU into order, (step 5) stack SKU on one of three rolling cages transported with the manually steered industrial truck, (step 6) document picking transaction for location *n* in the warehouse management system (WMS) via a touch display mounted on the industrial truck, and (step 7) travel to the subsequent pick location (return to the depot) *n+1*—for this, the relevant information is provided through the touch display. The elapsed time between steps (1) and (7) is measured exactly to the second and is used as the DV in the econometric model. Each order picker processes between 2,000 and

2,500 SKUs per day, with an average of 197 SKUs per batch. Figure 3 illustrates this OP process from the start of the time measurement on the left side across seven steps toward the end of the timekeeping on the right side.

Figure 3. OP process observed in the case study



3.2. Data collection and data cleaning

We analyze archival OP data collected between May and June 2021. The WMS utilized by the case company stores extensive log data on OP processes. We utilize such log data to construct a model capable of evaluating the impact of different storage systems on OP time as a major predictor of OP productivity. From the company's WMS, we extracted data including 221 order pickers with details on batch identification (ID), pick ID, picker ID, load unit ID, article number, number of units picked, volume of secondary SKU packaging, weight of the SKU, timestamps of each pick, and slot address per pick. Furthermore, we operationalized the travel distance through a distance matrix.

The raw picking events are created by the workers traveling through the warehouse, guided by a personal digital assistant. Each storage location has one unique identification number and stores exactly one SKU. All order pickers use the same model of industrial trucks, with a personal digital assistant mounted on them. The personal digital assistant provides information about (1) the SKU number, (2) the storage location identifier, (3) the quantity to pick, and (4) the storage location identifier for the next three picks. Once the order picker finds the correct location in the rack, one SKU is picked off the rack and stacked into the order. This process is confirmed by pressing “next” on the personal digital assistant, which generates the event “picked” in the database and triggers the visualization of the next storage location and SKU to be picked. Order pickers continue this way, SKU after SKU, until the order is completed. **Table 1** illustrates an exemplary dataset to outline which kinds of OP data are utilized.

Table 1. Format of example WMS data collected

date	batch ID	pick ID	picker ID	start	end	SKU ID	SKU	quantity	location	...
2022-06-01	123	1	987	10:03:14	10:03:44	337796	Pasta	2	01-001-01	...
2022-06-01	123	2	987	10:04:10	10:04:50	953226	Sauce	3	01-008-02	...
2022-06-01	123	3	987	10:06:08	10:06:21	935035	Wine	1	01-014-01	...
2022-06-01	123	4	987	10:08:24	10:09:00	801384	Water	4	01-019-02	...
...	...	...	...	...	...	...			...	...

An order placed by a grocery store is labeled with a batch ID when entering the WMS. This batch is assigned to exactly one-order picker ID through a first-come-first-serve method. One batch, also referred to as the picking list in the literature, contains several pick locations that need to be visited by the order picker. In our dataset, one line represents one pick location visited by the order picker, with every pick location storing exactly one SKU ID. An order picker visiting location 01-0001-01, where “pasta” is stored, may have to pick a varying quantity of the same SKU (e.g., two units of “pasta” in our case) (see Table 1).

Our initial dataset included 2,912,681 picks performed by 221 order pickers over five weeks. We excluded all operators with less than 1,000 cumulative picks to ensure a common experience level in the examination group. Furthermore, we control for speed when dividing travel distance by throughput time. Datasheets of industrial trucks were used to estimate the maximum speed of indoor forklift trucks, which equals 3.89 m/s, compared to 1.4 m/s for normal human walking speed. Note that this may depend on several factors, for example, indoor ambient conditions such as lighting or human operators' familiarity with their environment. After data cleaning, our final dataset included 2,357,976 picks performed by 192 order pickers.

4. Model for storage system comparison

4.1. Variables and measures

Our primary interest lies in evaluating the impact of the two different storage systems on OP time as a major outcome variable of OP systems. Therefore, our IV of interest is the respective storage system. We develop an econometric model where OP time is the DV. Additionally, we include several control variables (CVs) quantifying different aspects of the OP process (e.g., distance) to operationalize picker traveling.

Figure 4. The procedure for translating OP data into an econometric model

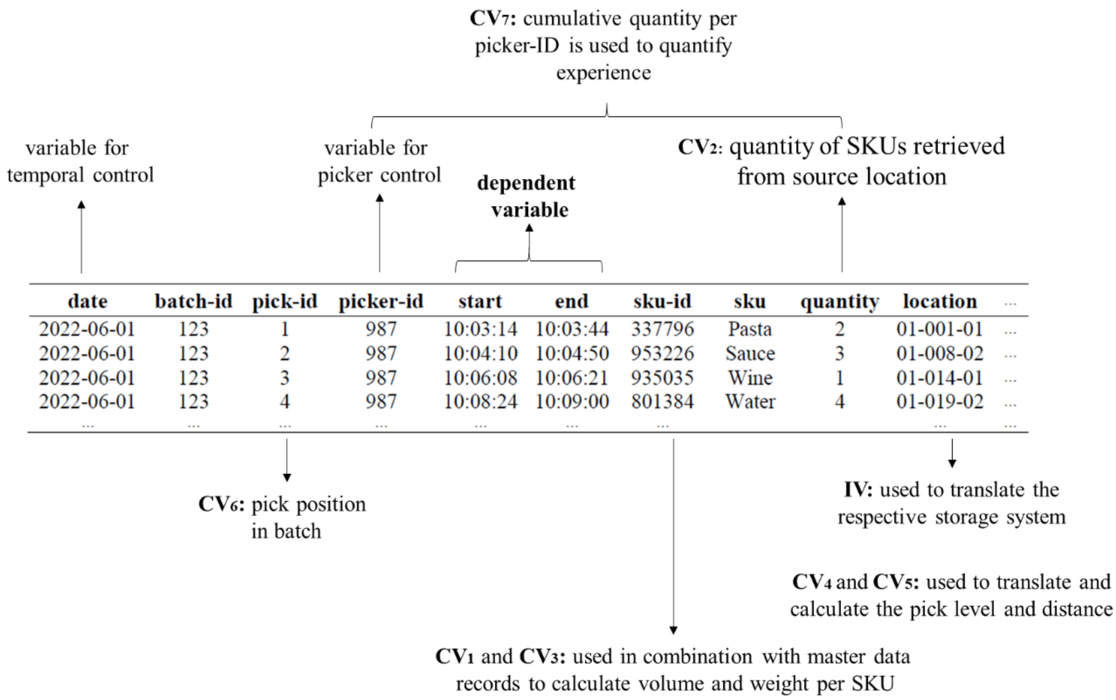


Figure 4 visualizes the procedure for translating the initial dataset into the constructs of the econometric model. One example of this translation is the location code used to translate whether the pick is retrieved from the full-pallet or high-density flow-rack storage system to quantify the IV. Additionally, the location code is used to calculate the pick level and the travel distance through a distance matrix.

Our DV is $\ln(picking\ time)_{ij}$ defined as the logarithmic transformation of the elapsed time in seconds needed to travel from storage location $\mathrm{i} - 1$ to storage location i and pick a given number of units of a SKU at storage location i by picker j. To measure OP time, we start a counter when the order picker confirms a pick on the pick list at location i – 1 by pushing “next” on the touch display mounted on the industrial truck (see Figure 3).

The device holds a constant wireless connection with the WMS, documenting relevant time stamps. The clock measurement ends after the picker has traveled to pick location i, has picked the SKU, and confirms the pick by pushing a symbol representing one of the three load units on the industrial truck. Both timestamps are used to calculate the total OP time, which we utilize as our DV. Such an OP time is operationalized as a continuous metric variable and is frequently used in OP research to evaluate performance in OP systems (Batt & Gallino, 2019; Matusiak et al., 2017).

The IV of interest quantifies whether the SKUs are retrieved from the full-pallet (coded as 0) or high-density flow-rack storage system (coded as 1). Therefore, we operationalize the storage systems with a binary dichotomous variable (Figure 2). We also include several CVs:

- (CV_1) *Volume per SKU:* As the SKU dimensions are relevant for the stacking process in manual OP, we integrate the volume per SKU as a continuous variable to control for the article dimensions impacting the complexity of the packing problem. The volume is measured in liters.
- (CV_2) *Quantity of SKU retrieved from source location:* Because the quantity of an SKU retrieved from a source location may vary from order to order, we integrate this factor as a CV.
- (CV_3) *Weight per SKU:* Because the weight of each SKU picked can impact the energy expenditure and metabolic costs of an order picker during the OP process (see Section 2.3), we integrate the weight in kilograms as a continuous variable.
- (CV_4) *Travel distance:* Manual picker-to-part systems require pickers to travel to dedicated SKU storage locations. Therefore, we integrate the travel distance from pick location to pick location as a continuous variable measured in meters. Because one line in our dataset represents one pick location visited by the order picker, we can operationalize the travel distance using a distance matrix.

- (CV_5) *Level:* The four different pick levels of the high-density flow-racks (see Section 3.1) are integrated as an additional CV.
- (CV_6) *Pick position in batch:* After an order picker grasps an SKU from a pick location, the SKU has to be sorted and stacked into an existing order (consisting of the previous pick positions). This could cause differences in height for manual material-handling tasks, including sorting and stacking.
- (CV_7) *Experience of order picker:* We integrate the cumulative picks per picker ID for the entire dataset to control for individual picker experience. The experience of the order picker is a continuous variable.

Table 2 summarizes the operationalization of our variables and provides relevant descriptive statistics.

Table 2. Operationalization of variables and descriptive statistics for our OP model

No.	Variable	description of operationalization	operationalization	mean	sd.
DV	Picking time per pick	Timestamps for the beginning and the end of the picking process are used to calculate the total event time in seconds	Continuous	21.88	17.61
IV	Storage system	0 = pick from full-pallet storage system 1 = pick from high-density flow-rack storage system	Binary dummy 0; n = 2,277,617 picks (96.98%) 1; n = 71,035 picks (3.02%)		
CV_1	Volume per SKU	Volume of the secondary package in liters	Continuous	8.83	7.11
CV_2	Quantity of SKU	Number of picks from one picking location	Continuous	11.34	19.18
CV_3	Weight per SKU	Weight in kilograms per SKU, including the SKU, primary packages, and secondary packages	Continuous	4.58	5.86
CV_4	Travel distance	Distance in meters from pick location to pick location	Continuous	6.87	8.75
CV_5	pick level	Pick level of the pick location	Continuous	1.20	0.44
CV_6	Pick position in the batch	One batch consists of several picks. This variable quantifies the position of a pick within the respective batch	Continuous	57.22	48.21
CV_7	Picker experience	Cumulative number of picks per order picker and in the dataset	Continuous	8,511.48	6,222.92

note: Descriptive statistics for the dataset after the data cleaning process with N = 2,348,652 picks were performed by 192 order pickers.

Next, we check for cross-correlation (Mills, 2011) and find no high correlations that would require excluding IVs (see Table 3). Thus, we can introduce all the presented variables into our econometric model.

Table 3. Correlation matrix

No.	DV	IV	CV_1	CV_2	CV_3	CV_4	CV_5	CV_6	CV_7
DV	1.00								
IV	-0.02	1.00							
CV_1	0.09	-0.08	1.00						
CV_2	0.16	-0.01	0.02	1.00					
CV_3	0.17	-0.07	0.19	0.18	1.00				
CV_4	0.24	-0.04	0.10	-0.02	0.01	1.00			
CV_5	-0.06	0.23	-0.18	-0.04	-0.21	-0.08	1.00		
CV_6	-0.02	0.05	0.12	-0.03	-0.17	-0.06	0.16	1.00	
CV_7	-0.06	0.01	-0.07	-0.15	-0.07	-0.01	0.04	0.01	1.00

Note: *p < 0.05; **p < 0.01; ***p < 0.001; N = 2,348,652 picks and 192 order pickers included.

4.2. Model development

As the first research question addresses OP time, we propose an event history analysis, also known as time-to-event analysis or survival analysis, summarizing statistical models concerned with questions on the timing and the duration until a given event occurs (Mills, 2011). Often applied in medical research, an event can be represented by mortality (death vs. still alive at last observation), for example, when studying the survival of patients according to their first referral decision in cancer treatment (Bouquet et al., 2021). An event is formally defined as the instantaneous transition from origin to destination (Oud, 2014). In a nutshell, such AFTMs are regression models with different likelihood estimators than ordinary least-square regressions and use event time or survival time as the DV (Mills, 2011).

We transfer this logic to the OP context and propose an AFTM to estimate the impact of different storage systems (IV) on OP time (DV). This is inspired by the landmark paper of

Batt and Gallino (2019). In AFTM, T represents the time-to-event or survival time, which we translate to the general OP context as OP 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, log-normal, or log-logistic). The choice of the parametric distribution assumed in the AFTM is made by comparing the model fit for a variety of different distributions through, for example, the Akaike information criterion (AIC), the Bayesian information criterion (BIC), or the log-likelihood ratio (LL).

In the proposed econometric model, the DV is denoted as T and is defined as the elapsed time between the beginning and end of a picking process performed by an order picker. Because AFTMs 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). We define n independent predictor variables x_n and their corresponding regression coefficients β_n. Additionally, ε represents the error term assumed to have a particular parametric distribution.

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

The coefficient in the parametric AFTM can be interpreted as follows: A positive coefficient indicates that the log duration time increases, leading to longer duration times. A negative coefficient indicates that the log duration time decreases, leading to shorter duration times. To ease the interpretation of our estimates, we need to transform them. In AFTM, this transformation depends on the assumption of the DV. With our log-logistic AFTM, we apply the following transformation (Mills, 2011):

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

Our IV of interest is dummy-coded as either a pick from a high-density flow-rack storage system or from the other storage system. Integrating these variables into the AFTM, we formulate and apply the following parametric model:

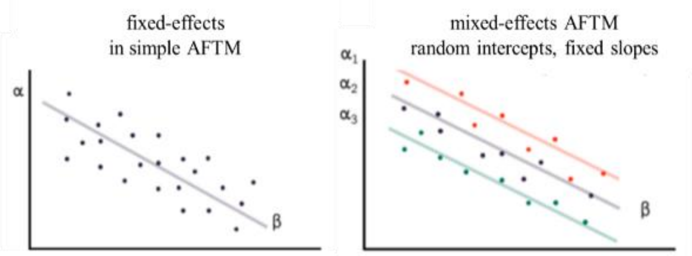
$$\ln(\textit{picking time}) = \alpha_0 + \textit{volume per SKU}\ \beta_1 + \textit{quantity of SKUs}\ \beta_2 + \textit{weight per SKU}\ \beta_3 + \textit{travel distance}\ \beta_4 + \textit{pick level}\ \beta_5 + \textit{pick position in batch}\ \beta_6 + \textit{picker experience}\ \beta_7 + \textit{storage system}\ \beta_8 + \textit{order picker}\ \beta_9 + \textit{temporal control}\ \beta_{10} + \varepsilon, \quad (3)$$

where we dummy-code the storage system as

$$\textit{storage system} = \begin{cases} 1 & \textit{if the pick is retreived from a high} - \textit{density rack system,} \\ 0 & \textit{otherwise.} \end{cases} \quad (4)$$

Additionally, we formulate a mixed-effects AFTM where we allow one regression line per order picker with random intercepts and fixed slopes. A similar approach was applied by Matusiak et al. (2017) when applying a multilevel model to an OP dataset similar to ours. Figure 5 illustrates the difference between simple AFTM and mixed-effects models, where we apply a methodological integration of individual order picker heterogeneity (see Section 2.3 and the applied CV picker experience, for example).

Figure 5. Methodological integration of order picker heterogeneity through a mixed-effects AFTM



5. Results

We estimate the model proposed in Formulas (3) and (4) for 2,357,976 observation points representing manual picks and apply the survival package in R (Therneau et al., 2022; Therneau & Grambsch, 2000). The results are presented in Table 4.

Table 4. Results of the log-logistic AFTM for the impact of storage systems on OP time

Dependent variable: OP time				
	Model 1	**Model 2**	**Model 3**	**Model 4**
HDFRSS			-0.0471*** (0.0026)	-0.0347*** (0.0086)
Volume per SKU	0.0032*** (0.0001)	0.0030*** (0.0001)	0.0030*** (0.0001)	0.0027*** (0.0001)
Quantity of SKU	0.0050*** (0.00003)	0.0052*** (0.00003)	0.0052*** (0.00003)	0.0054*** (0.00003)
Weight per SKU	0.0185*** (0.0001)	0.0185*** (0.0001)	0.0185*** (0.0001)	0.0181*** (0.0001)
Travel distance	0.0262*** (0.0001)	0.0264*** (0.0001)	0.0263*** (0.0001)	0.0260*** (0.0001)
Pick level	0.0051*** (0.0009)	0.0076*** (0.0009)	0.0108*** (0.0009)	0.0098*** (0.0009)
Pick position in batch	0.0007*** (0.00001)	0.0006*** (0.00001)	0.0006*** (0.00001)	0.0006*** (0.00001)
Experience	-0.000004*** (0.000000)	-0.000004*** (0.000000)	-0.000004*** (0.000000)	-0.000001*** (0.000000)
HDFRSS × Volume per SKU				0.0226*** (0.0005)
HDFRSS × Quantity of SKU				-0.0089*** (0.0003)
HDFRSS × Weight per SKU				0.0340*** (0.0009)
HDFRSS × Travel distance				0.0155*** (0.0004)
HDFRSS × Pick level				-0.0105*** (0.0037)
HDFRSS × Pick position in batch				0.0023*** (0.0001)
HDFRSS × Experience				-0.00003*** (0.000000)
Temporal fixed effects	included	included	included	included
Picker fixed effects	not included	included	included	included
Constant	2.4619*** (0.0012)	2.4551*** (0.0012)	2.4554*** (0.0012)	2.4618*** (0.0012)
Observations	2,357,976	2,357,976	2,357,976	2,357,976
Order pickers	192	192	192	192
AIC	18,133,437	18,074,234	18,073,913	18,061,955
BIC	18,133,551	18,076,769	18,076,461	18,064,591
LL	-9,066,709	-9,036,917	-9,036,756	-9,030,769
Deg. of freedom	7	199	200	207
Chi-square	377,566 ***	384,923 ***	385,246 ***	397,219 ***

note: HDFRSS = High-density flow-rack storage system; robust standard errors in parentheses; 192 order pickers included; *p < 0.05; **p < 0.01; ***p < 0.001; an additional test regarding the distribution assumption in our DV testing Weibull, Gaussian, logistic, log-normal, and log-logistics is attached in Appendix 1.

We draw the reader's attention to Model 1, where we integrate OP time as our DV together with all CVs. The coefficients for volume per SKU, quantity of SKUs, weight per SKU, travel distance, pick level, and pick position in the batch are positive, indicating that they increase OP time and therefore decelerate the process (Table 4, Model 1, lines 2–6). With respect to travel distance, we can transform the estimator β_4 by applying Formula (2), and we find that every additional meter of traveling increased OP time by up to 2.65% ($\beta_4 = 0.0262$, $p < 0.001$). In contrast, the coefficient for the cumulative experience of order pickers is negative, indicating that experience decreases OP time and therefore accelerates the process. With every additional 100 picks, the OP decreases by 0.039% ($\beta_7 = -0.000004$, $p < 0.001$).

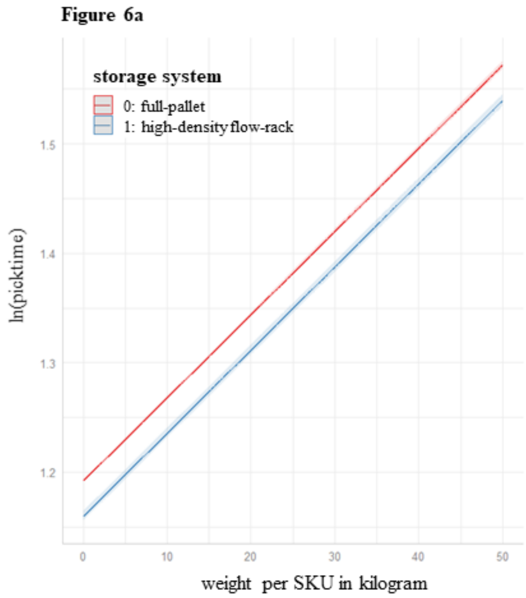
Next, we compare the impact of a methodological integration of order picker heterogeneity through a mixed-effects AFTM. While Model 1 is a simple AFTM, Model 2 allows one regression line per order picker as a mixed-effects AFTM. We find that the model fit improves as the AIC (from 18,133,437 in Model 1 to 18,074,234 in Model 2) and BIC (from 18,133,551 in Model 1 to 18,076,769 in Model 2) decrease significantly. The LL is reduced from -9,066,709 in Model 1 to -9,036,917 in Model 2, validating the improvement of the model fit. Therefore, we note that order picker heterogeneity is an important variable for explaining the performance of manual OP systems.

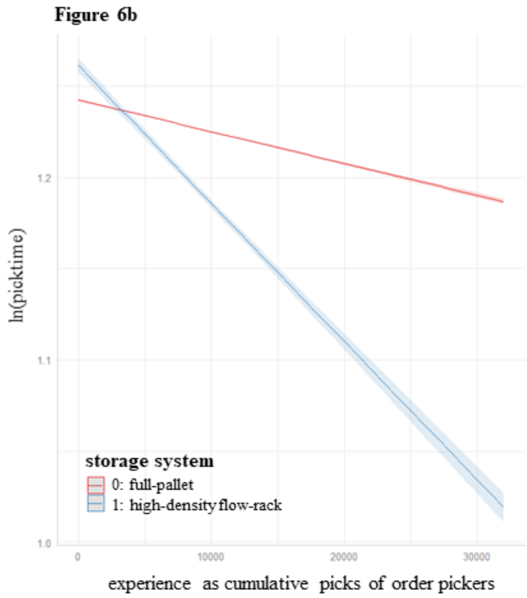
For the evaluation of storage systems, we draw the reader's attention to Model 3, where we integrate our IV of interest into the mixed-effects AFTM and highlight two interesting findings. First, the fit of Model 3 (which differentiates between storage systems) improves compared to Model 2 (which does not differentiate between storage systems), and we conclude that the type of storage system used is an important predictor of OP time in manual OP systems. Second, when keeping all CVs constant, the high-density flow-rack storage system decreases the OP time by up to 4.60% ($\beta_8 = 0.0471$, $p < 0.001$) compared to the full-pallet storage system and, therefore, is capable of accelerating the OP process. However, the drivers of this acceleration remain unknown until this point and require the investigation of interaction terms for subsequent moderation analysis, where the storage system represents our moderator. The results are presented in Model 4.

Our starting point for the moderation analysis is the weight per SKU. The coefficient for weight per SKU is positive ($\beta_3 = 0.0340$, $p < 0.001$), indicating that the heavier an SKU, the longer the pick time. This seems reasonable in light of the metabolic costs that increase with the load picked and carried by an order picker. We find a similar logic for the interaction term HDFRSS × weight per SKU ($\beta = 0.0181$, $p < 0.001$), indicating that when an SKU is retrieved from a high-density flow-rack storage system, the heavier an SKU, the longer the pick time. Thus, the direction of the effect is identical for the high-density flow-rack storage system and the full-pallet storage system. We visualize this through simple slopes in Figure 6, where the diagram on the left side includes the weight per SKU. In a nutshell, simple slopes are regression lines at one level of a predictor, which is the weight per SKU in this case. Because the regression lines have identical slopes, the storage system does not moderate the impact of weight per SKU on OP time. Weight per SKU is, therefore, relevant for both storage systems and is probably more dependent on human factors, such as physical strength or physical condition.

Looking at the experience of order pickers, we find significantly different slopes in the right graph of Figure 6 and a moderating role of storage systems that we can interpret as follows: when picking from high-density flow-rack storage systems, the effect of order picker experience on OP time is stronger than for full-pallet storage systems. Figure 6 visualizes the simple slopes for the moderator storage system with weight per SKU (Figure 6a) and experience (Figure 6b). In Figure 6b, we identify a crossover effect in which the effect of experience on the DV OP time switches at about 4,000 cumulative picks. We can derive that picking from high-density racks takes longer for inexperienced pickers (less than 4,000 cumulative picks) than picking from full pallets. This can possibly result from the search task in the high-density racks, where 20 dissimilar SKUs are stored nearby.

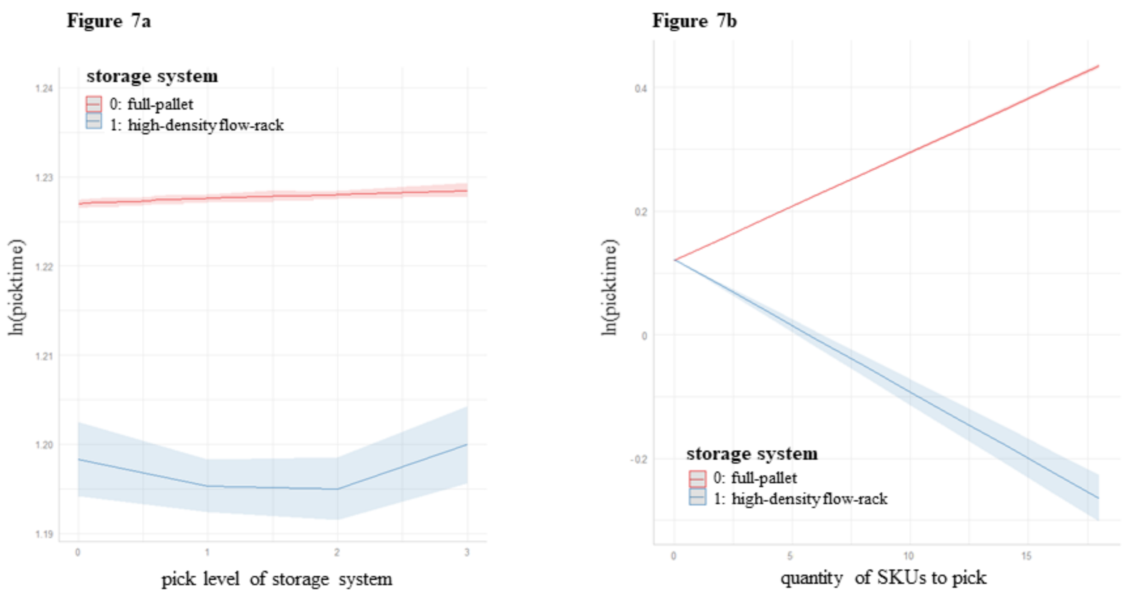
Figure 6. Simple slopes for the moderator storage system with weight (left) and experience (right) as IVs





Next, we further investigate the pick level of the storage system and the interaction terms in Model 4, presented in Table 4. The coefficient for the pick level is positive for all picks ($\beta_5 = 0.0098$, $p < 0.001$), indicating that the higher the pick level, the longer the OP time. However, the direction of this effect turns to a negative coefficient in high-density flow-rack storage systems × pick level ($\beta_5 = -0.0105$, $p < 0.001$), indicating that the higher the pick level, the shorter the OP time. At this point, we recall the four levels of the high-density flow storage system (0.00, 0.60, 1.20, and 1.80 meters from the floor). Level 2 at 1.20 meters represents the golden zone where SKUs are located at the height between most pickers' waists and shoulders. Therefore, we assume a non-linear relationship and integrate a polynomial term for our moderation testing for a U-shaped moderation effect of the storage system by (storage systems × pick level).[2] We draw the reader's attention to **Figure 7** (left diagram), which verifies the previous assumptions. When picking from high-density flow-rack storage systems, the effect of pick level on OP time is non-linear and follows a U-shape. The ground level and Level 3, which are 1.80 meters in height, require time-consuming bending and stretching. The OP time decreases when retrieving SKUs from Levels 2 and 3 of the high-density flow-rack storage system.

Figure 7. Simple slopes for the mediator storage system with weight (left) and experience (right) as IVs



Finally, the largest difference between the two storage systems under examination results from the number of SKUs to pick. In Model 4, the coefficient for the quantity of SKUs is positive for all picks (β_5 = 0. 0.0054, $p < 0.001$), indicating that the higher the quantity of SKUs, the longer the OP time. However, the direction of this effect turns to a negative coefficient in high-density flow-rack storage systems × quantity of SKUs (β_5 = -0.0089, $p < 0.001$), indicating that the higher the quantity of SKUs, the shorter the OP time. The simple slopes for the moderating role of storage systems are visualized in Figure 7 (right diagram).

With an increasing quantity of SKUs to pick, the OP time increases for full-pallet flow-rack storage systems but decreases for high-density flow-rack storage systems.

6. Further analyses

6.1. Replenishment of different storage systems

Although we find that high-density flow-rack storage systems can reduce the OP time by 4.60%, this storage system may increase the replenishment time compared to full-pallet storage systems. This concern is motivated by the fact that replenishing high-density flow-rack storage systems increases the number of manual activities—for separating SKUs from a unit load and sorting individual SKUs into the system. To assess the overall impact of the high-density flow-rack storage system on the OP process, we quantify the replenishment process through a second mixed-effects log-logistic AFTM. The formulation is as follows:

$$\ln(retrieval\ time) = \alpha_0 + \ travel\ distance\ \beta_1 + \ storage\ height\ \beta_2 + SKUs\ on\ palette\ \beta_3 + \ volume\ per\ palette\ \ \beta_4 + \ operator\ experience\ \ \beta_5 + storage\ system\ \beta_6 + \ forklift\ operator\ \beta_7 + \ temporal\ control\ \beta_8 + \varepsilon, \qquad (5)$$

where we dummy-code the storage system as follows:

$$storage\ system = \begin{cases} 1\ if\ the\ pick\ is\ retreived\ from\ a\ high-density\ rack\ system, \\ 0\ otherwise. \end{cases} \qquad (6)$$

We empirically test our model with a second archival dataset on replenishment operations covering identical time frames and warehouses. The dataset includes 98,625 retrieval operations performed by 31 forklift operators. Details of the operationalization of our variables and descriptive statistics are provided in Appendix 2. We also test for cross-correlation in Appendix 3.

We now draw the reader’s attention to Table 5. Similar to the OP case, we observe the best model fit with the methodological integration of order picker heterogeneity through a mixed-effects AFTM. When keeping all variables constant, we find that replenishment operations of a high-density flow-rack storage system (β_6 = -0.3848) are associated with a 38.48% increase in the expected replenishment time and therefore decelerate the process.

Table 5. Results of log-logistic AFTM for retrieval time

Dependent variable: Retrieval time per pallet				
	Model (5)	**Model (6)**	**Model (7)**	**Model (8)**
Storage system (IV)		0.439233^{***} (0.006884)		0.384883^{***} (0.006788)
Volume per pallet	0.003511^{***} (0.000064)	0.003446^{***} (0.000063)	0.003648^{***} (0.000061)	0.003583^{***} (0.000060)
SKU on pallet	0.023040^{***} (0.000727)	0.026206^{***} (0.000714)	0.019191^{***} (0.000684)	0.021802^{***} (0.000679)
Travel distance	-0.000597^{***} (0.000060)	-0.000795^{***} (0.000067)	-0.000481^{***} (0.000063)	-0.000665^{***} (0.000067)
Storage height	-0.000198^{***} (0.000005)	-0.000093^{***} (0.000005)	-0.000167^{***} (0.000005)	-0.000082^{***} (0.000005)
Forklift operator experience	-0.000021^{***} (0.000001)	-0.000020^{***} (0.000001)	-0.000014^{***} (0.000001)	-0.000012^{***} (0.000001)
Operator fixed effect	No	Yes	No	Yes
Constant	4.834118^{***} (0.005991)	4.689332^{***} (0.006232)	4.834725^{***} (0.005723)	4.715754^{***} (0.005979)
Observations	98,625	98,625	98,625	98,625
Forklift operator	31	31	31	31
AIC	1,114,536	1,110,644	1,108,686	1,105,579
BIC	1,114,603	1,110,720	1,109,037	1,105,940
LL	-557,261	-555,314	-554,305	-552,751
Chi^2	$6,789.161000^{***}$ (df = 5)	$10,683.650000^{***}$ (df = 6)	$6,547.251000^{***}$ (df = 5)	$9,656.338000^{***}$ (df = 6)

note: Robust standard errors in parentheses; 31 forklift operators included; *p < 0.05; **p < 0.01; ***p < 0.001; an additional test regarding the distribution assumption in our DV testing Weibull, Gaussian, logistic, log-normal, and log-logistics is attached in **Appendix 4**.

Summarizing the best Model (8), high-density flow-rack storage systems can decrease the throughput time by up to 4.60% but increase the processing time for replenishments by up to 38.65%. Obviously, an economic metric is needed to evaluate and compare these interdependencies; the replenishment part is required to be able to complete a picking process. We discuss a possible connecting concept in the next section.

6.2. A holistic economic perspective on high-density flow-rack storage systems

When setting both these material flow perspectives in contrast, it is possible to derive an optimal economic replenishment quantity (ERQ), representing the minimum replenishment quantity that makes the system economically feasible. In other words, we search for the quantity that offsets the increased replenishment times by the reduced picking times for each SKU stored in the high-density flow-rack system. For each SKU, the ERQ can be computed by considering the differences in both the replenishment and picking times between the high-density flow-rack system and the full-pallet storage system. The notation used in the ERQ computation is introduced in Table 6.

Table 6. ERQ notation

Symbols	Description
i	SKU index, $I = 1 \dots N$
ERQ_i	Economic replenishment quantity for the high-density flow-rack system for SKUi
$\#PL_i$	Number of picking locations dedicated to SKU*i* in the traditional system
$t_{R,i}^{HD}$	Unit replenishment time of the high-density flow-rack system for an SKU of *i*
$t_{P,i}^{HD}$	Unit picking time from the high-density flow-rack system for an SKU of *i*
$t_{R,i}^{TS}$	Unit replenishment time of the traditional system for a pallet of *i*
$t_{P,i}^{TS}$	Unit picking time from the traditional system for an SKU of *i*
D_i^T	Demand of *i* in a reference time period *T* measured in SKUs
$\#\frac{SKU_i}{PL}$	Number of SKUs of *i* per pallet
d^{HD}	Channel depth in the high-density flow-rack system
d_i	Depth of *i*

We propose a first ERQ formulation per SKUi, ERQ_i, which we define as the minimum replenishment quantity for which the difference in the total picking and replenishment times of the high-density flow-rack system and the traditional pallet-sized rack storage system is smaller or equal to zero (7).

$$t_{R,i}^{HD} \cdot \frac{D_i^T}{ERQ_i \cdot \#\frac{SKU_i}{PL}} + t_{P,i}^{HD} \cdot D_i^T - \left(t_{R,i}^{TS} \cdot \frac{D_i^T}{\#PL_i \cdot \#\frac{SKU_i}{PL}} + t_{P,i}^{TS} \cdot D_i^T \right) \leq 0 \tag{7}$$

Interpreting (7) as an equation, the ERQ_i can be derived as follows:

$$ERQ_i = \frac{t_{R,i}^{HD} \cdot \#PL_i}{t_{R,i}^{TS} + \left(t_{P,i}^{HD} + t_{P,i}^{TS} \right) \cdot \#PL_i \cdot \#\frac{SKU_i}{PL}} \tag{8}$$

It is important to note that ERQ_i must be compared to the total shelf space available in the high-density flow-rack (9). In fact, the overall time performance improvement enabled by the high-density flow-rack system can only be achieved when the system can accommodate the ERQ_i for each SKU under analysis on the shelf.

$$ERQ_i \leq \frac{d^{HD}}{d_i} \tag{9}$$

Picking and replenishment times are not the only factors that might affect the ERQ choice, as the ERQ affects the total warehouse space occupied by the high-density flow rack, and being related to the total size of the system, it also affects the rack investment cost. Thus, we introduce a more holistic economic evaluation when computing the ERQ that takes into account the different warehouse costs affected by this measure.

For this purpose, a cost optimization model is proposed that accounts for the overall warehouse picking system. This is intended to support the decision of which SKU to store inside the high-density flow-rack system, and the correspondent ERQ_i, to minimize the total cost of the warehouse picking area, including both the high-density flow-rack system and the full-pallet system. The additional notation used for the cost optimization model is introduced in Table 7.

Table 7. Cost optimization model notation

Symbols	Description
x_i^{HD}	Binary variable equal to 1 if the SKU*i* is stocked in the high-density flow-rack system and 0 if the SKU*i* is stocked in the traditional system
NL^{HD}	Number of levels of the high-density flow-rack system
l^{HD}	Channel length in the high-density flow-rack system
h^{HD}	Channel height in the high-density flow-rack system
l_i	Length of SKU*i*
h_i	Height of SKU*i*
c_R	Hourly cost of the operator and the material handling in the reserve area
c_P	Hourly cost of the operator in the picking area
c_S	Monthly cost per square meter of the warehouse
c_B^{HD}	Unit rack investment cost per square meter of the high-density flow-rack system
c_B^{TS}	Unit rack investment cost per square meter of the traditional system
RT_{max}^T	Total available replenishment time in hours in a reference time period *T*
PT_{max}^T	Total available picking time in hours in a reference time period *T*

The total cost under analysis consists of four terms: replenishment cost, picking cost, space cost, and rack investment cost. The *replenishment cost* measures the cost associated with the replenishment of the picking area, including both high-density flow-rack and the traditional system (Calzavara et al., 2017)Klicken oder tippen Sie hier, um Text einzugeben.. This cost depends on the time required to replenish an SKU in the high-density flow-rack system $t_{R,i}^{HD}$ on the time required to replenish a pallet in the traditional system, $t_{R,i}^{TS}$, on the number of replenishment for both the high-density flow-rack system and traditional systems $\frac{D_i^T}{ESQ_i \cdot \#\frac{SKU_i}{PL}}$ and $\frac{D_i^T}{\#PL_i \cdot \#\frac{SKU_i}{PL}}$, respectively, and on the hourly cost of the material handling equipment and the operator performing this task c_R. The *picking cost* consists of the time needed to physically pick the SKUs from the two systems $t_{P,i}^{HD}$ and $t_{P,i}^{TS}$, multiplied by the operator hourly cost c_P (Calzavara et al., 2019). Other fixed picking time components associated with activities such as reading the pick list, setting up the order, searching for an SKU, or scanning barcodes were excluded from this analysis, as they were not different between the two systems. *Space cost* refers to the space occupied by both the high-density flow-rack and the traditional systems, multiplied by the monthly cost per square meter of the warehouse c_S. The space occupied by the traditional systems consists of the sum of all the picking locations $\#PL_i$ of the SKUs stored in this system, assuming one pallet per picking location. We assume only one picking level (i.e., picking from the ground level of the system). For the high-density flow-rack system, we assume a fixed number of levels per channel NL^{HD}, with a fixed channel size, and each channel dedicated to a single SKU*i*. Thus, the total space occupied by the high-density flow-rack depends on the number of SKUs stored at the ground level of the system. Finally, the *rack investment cost* refers to the cost of the building of the two systems, which depends on the space occupied by each system multiplied by the corresponding unit rack investment cost.

The proposed optimization model is constructed as a mixed-integer programming model and is presented below.

$$min \ \sum_i \left(c_R \cdot \left(x_i^{HD} \cdot t_{R,i}^{HD} \cdot \frac{D_i^T}{ERQ_i * \# \frac{SKU_i}{PL}} + (1 - x_i^{HD}) \cdot t_{R,i}^{TS} \cdot \frac{D_i^T}{\#PL_i \frac{SKU_i}{PL}} \right) + c_P \cdot \left(x_i^{HD} \cdot t_{P,i}^{HD} * D_i^T + (1 - x_i^{HD}) \cdot t_{P,i}^{TS} \cdot D_i^T \right) + c_S \cdot \left(\frac{\sum_i x_i^{HD}}{NL^{HD}} \cdot l^{HD} \cdot d^{HD} + \sum_i \#PL_i \cdot l^{TS} \cdot d^{TS} \right) + c_B^{HD} \cdot \frac{\sum_i x_i^{HD}}{NL^{HD}} \cdot l^{HD} \cdot d^{HD} + c_B^{TS} \cdot \sum_i \#PL_i \cdot l^{TS} \cdot d^{TS} \right) \tag{10}$$

$$s.t. \quad \sum_i \left(x_i^{HD} \cdot t_{R,i}^{HD} \cdot \frac{D_i^T}{ERQ_i * \# \frac{SKU_i}{PL}} + (1 - x_i^{HD}) \cdot t_{R,i}^{TS} \cdot \frac{D_i^T}{\#PL_i * \# \frac{SKU_i}{PL}} \right) \leq RT_{max}^T \tag{11}$$

$$\sum_i (x_i^{HD} \cdot t_{P,i}^{HD} \cdot D_i^T + (1 - x_i^{HD}) \cdot t_{P,i}^{TS} \cdot D_i^T) \le PT_{max}^T \quad (12)$$

$$x_i^{HD} \cdot ERQ_i \cdot d_i \le d^{HD} \qquad \forall\, i \in I \quad (13)$$

$$x_i^{HD} \cdot l_i \le l^{HD} \qquad \forall\, i \in I \quad (14)$$

$$x_i^{HD} \cdot h_i \le h^{HD} \qquad \forall\, i \in I \quad (15)$$

$$x_i^{HD} \cdot ERQ_i + (1 - x_i^{HD}) \cdot \#PL_i \cdot \# \frac{SKU_i}{PL} = D_i^T \qquad \forall\, i \in I \quad (16)$$

$$x_i^{HD} = \{1; 0\} \qquad \forall\, i \in I \quad (17)$$

$$ERQ_i\ , \#PL_i \in N \qquad \forall\, i \in I \quad (18)$$

Model variables include a binary variable x_i^{HD} equal to 1 if an SKU is stored in the high-density flow-rack or equal to 0 if the SKU is stored in the traditional system, the ERQ_i, for each SKU stored in the high-density flow-rack system and the number of pallet locations per each SKU stored in the traditional system, $\#PL_i$.

The objective function (10) minimizes the total cost of the warehouse picking area, including both the high-density flow-rack system and the traditional system. Constraint (11) states that the total time needed for the replenishment activity for both the high-density flow-rack system and the traditional system must be lower than the total available replenishment time, while constraint (12) indicates that the total picking time needed for the picking activity of both the high-density flow-rack system and the traditional system must be lower than the total available picking time. Constraints (13), (14), and (15) are space constraints, ensuring that the size of SKU*i* fits the channel size of the high-density flow-rack system. Constraint (16) ensures that the quantity of SKU*i* at stock is enough to satisfy the demand of SKU*i* in reference period T. Finally, constraints (17) and (18) set variable constraints, including the binary variable, which can assume only 1 or 0 values, and ERQ_i and $\#PL_i$ that can assume only integer values per each SKUi.

7. Conclusions and further research

7.1. Summary of this work

This work evaluated the impact of two alternative storage system designs on the performance of OP systems. We were concerned with the high-density flow-rack storage system, where 20 different SKUs were stored on the ground floor in an area corresponding to the size of three pallets. The final dataset included 2,348,652 operations performed by 192 operators over five weeks to answer RQ_1 *How does the use of flow-rack storage systems influence OP time?* and RQ_2 *How does individual order picker heterogeneity influence the relative performance of flow-rack storage systems?*

The analysis showed that high-density flow-rack storage systems could accelerate the picking process, in the case of the B&M retailer investigated in this paper, by 4.60%, resulting in a smoother flow of materials compared to standard storage systems. The impact on replenishment time was quantified using a second log-logistic AFTM for forklift drivers with random intercepts and fixed slopes as a mixed-effects model. With a log-logistic distribution assumption of the dependent time variable and holding all other variables constant, we found that the replenishment operation slowed down the process by 38.65%.

In an effort to balance both time tendencies we identified for the high-density flow-rack system, we specified which SKU should be stored in this system together with the optimal ERQ per SKU. In Section 6.2, a mixed-integer optimization model was proposed, which minimizes the total costs affected by these two variables, including replenishment cost, picking cost, space cost, and investment cost.

7.2. Implications to theory

Our study relates to several streams of literature. First, we contribute to the literature on storage assignment decisions and investigate the trade-offs between full-pallet storage systems and high-density flow-rack storage systems. Battini et al. (2018) defined the unitary picking time for cases in which cartons are picked from racks or pallets as the major input variables for the storage assignment model. Using data collected in a case study, we show that picking from high-density flow-rack storage systems is 4.60% faster than picking from full-pallet storage systems. Second, we contribute to the literature that has investigated the determinants of OP time, such as Finnsgård et al. (2011) or Finnsgård and Wänström (2013). Similar to Finnsgård and Wänström (2013), we find that height of exposure (in our case, the pick level) and part size (in our case, the volume of an SKU) increase OP time. We extend their model with the variable pick position in the batch, quantifying the complexity of the underlying packing problem (Dowsland & Dowsland, 1992; Dyckhoff, 1990). Third, we contribute to the literature on human learning in OP (e.g., Grosse et al. [2013], Batt and Gallino [2019], and Loske [2022]. Our empirical results for the underlying industrial case study indicate that when a picker completes 1,000 picks, OP time decreases by up to 0.45%. Additionally, we empirically verify that the storage system moderates the impact of experience on OP time. To the best of our knowledge, our study is the first to empirically validate such a moderating effect.

By evaluating the performance of human pickers for two different OP systems, this paper contributes to an emerging stream of research that investigates human factors in a logistics context. The results provide evidence that human factors are crucial for the performance of work systems and that they therefore need to be a core part of research and business design initiatives.

7.3. Managerial implications

This research has several implications for practice. First, the results of the AFTM models provide managers with warehouse and SKU attributes that have the potential to improve the performance of human order pickers—if considered appropriately in the design and operation of the warehouse. Second, the economic evaluation of the two types of picking systems suggests that the improvement in picking time offered by the high-density flow-rack compared to the traditional system might be offset by increased replenishment times. Thus, the system must be carefully sized to guarantee an improvement in the overall cost situation. This is relevant for warehouse managers when designing the warehouse picking area. To support warehouse managers in this task, a simple economic replenishment quantity model was proposed for a high-density flow-rack system that considers both replenishment and picking time.

7.4. Limitations and further research

The empirical analysis provided in this paper has broad transfer potential to several areas of human–technology interaction in production and logistics contexts. However, the empirical results presented in the previous sections have limitations that need to be considered. In turn, they spawn new research avenues for practice-relevant research for retail operations. Our first limitation is the varying level of employment time for each operator investigated in our analysis. Order pickers could have varying levels of experience obtained prior to the experiment, which was not captured in our dataset. Therefore, further research could be dedicated to the question of learning curves related to different storage systems when a temporary workforce is employed.

Second, Finnsgård and Wänström (2013) provided empirical evidence of the critical impact of SKU packaging on OP time. Although we integrated the volume and weight of SKUs, the secondary packing could have been designed differently (e.g., fully enveloping the secondary packing or varying the thickness of the carton box for the secondary packing). We did not integrate the secondary packing system design variables into our model, which could be another interesting extension of our empirical examinations.

Specific attention should be paid to issues of technology design and application, for example, which systems are most efficient in which settings, including the characteristics and structure of the human workforce, as well as the order quantities and schedules involved. This would support a valuable theory modeling perspective as well as a business practice design configuration perspective on human–technology interaction in sociotechnical operations systems. Such an analysis could contribute to a larger economic sustainability perspective and should be complemented by social and ecological sustainability analyses on the issue at hand.

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Appendix

Appendix 1: Test for the distribution assumption of order picking time in the order picking model

Dependent variable: Picking time	**Weibull**	**Tobit**	**Logistic**	**Log-normal**	**Log-logistic**
Storage system (IV)	0.0017 (0.0027)	-0.7078*** (0.0603)	-0.9861*** (0.0466)	-0.0592*** (0.0026)	-0.0471*** (0.0026)
Volume per SKU	0.0052*** (0.0001)	0.0839*** (0.0016)	0.0554*** (0.0013)	0.0034*** (0.0001)	0.0030*** (0.0001)
Number of picks	0.0051*** (0.00003)	0.1355*** (0.0006)	0.1358*** (0.0007)	0.0043*** (0.00003)	0.0052*** (0.00003)
Weight per SKU	0.0144*** (0.0001)	0.4132*** (0.0020)	0.3755*** (0.0017)	0.0177*** (0.0001)	0.0185*** (0.0001)
Travel distance	0.0103*** (0.00003)	0.4899*** (0.0012)	0.5324*** (0.0011)	0.0241*** (0.0001)	0.0263*** (0.0001)
Pick level	-0.0167*** (0.0010)	0.0635*** (0.0221)	0.2724*** (0.0169)	0.0012 (0.0009)	0.0108*** (0.0009)
Number of picks per batch	0.0001*** (0.00001)	0.0084*** (0.0002)	0.0109*** (0.0002)	0.0004*** (0.00001)	0.0006*** (0.00001)
Picker experience	-0.000004*** (0.000000)	-0.0001*** (0.000002)	-0.00004*** (0.000001)	-0.000004*** (0.000000)	-0.000004*** (0.000000)
Picker fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	2.9463*** (0.0013)	13.6425*** (0.0295)	10.9352*** (0.0236)	2.5059*** (0.0013)	2.4554*** (0.0012)
Observations	2,357,976		2,357,976	2,357,976	2,357,976
Picker	192	192	192	192	192
AIC	18,611,897	19,844,348	19,232,064	18,130,474	18,073,913
BIC	18,614,445	19,846,896	19,234,612	18,133,021	18,076461
LL	-9,305,748	-9,921,973	-9,615,831	-9,065,036	-9,036,756
chi^2 (df = 8)	204,813.0000***	277,947.2000***	365,177.7000***	326,495.5000***	385,246.6000***

Note: Robust standard errors in parentheses; 192 order pickers included; *p < 0.05; **p < 0.01; ***p < 0.001. Lowest AIC and BIC and best LL for log-logistic AFTM.

Appendix 2: Operationalization of variables and descriptive statistics for the retrieval model.

No.	Variable	Description of operationalization	Operationalization	Mean	SD.
DV	Retrieval time per palette	Timestamps for the begin and the end of the retrieval process are used to set the borders of the total ever time	Continuous	138.51	78.99
IV	Storage system	0 = Pick from EUL1 storage system 1 = Pick from high density storage system	Binary dummy 1 = chest level (7.85%), 0 = ground level (92.15%)		
CV_1	Volume per palette	Volume of a full unit retrieved from the reserve area	Continuous	922.65	443.23
CV_2	SKU on palette	Number of SKU on the palette	Continuous	782.29	750.48
CV_3	Travel distance	Distance in meters from location to locatic travelled by the forklift operator.	Continuous	22.71	39.48
CV_4	Storage height	Height of the reserve area where the full palette is retrieved.	Continuous	5.04	2.53
CV_5	Forklift operator experience	Cumulative number of retrieval operations per forklift operator in the dataset	Continuous	2145	1508

Note: Descriptive statistics for the dataset after the data cleaning process with N=98,625 retrieval operations performed by 31 forklift operators.

Appendix 3: Correlation matrix for the retrieval model.

No.	DV	IV	CV_1	CV_2	CV_3	CV_4	CV_5
DV	1.00						
IV	0.19	1.00					
CV_1	0.07	0.05	1.00				
CV_2	- 0.12	0.08	0.13	1.00			
CV_3	0.00	- 0.04	- 0.05	0.06	1.00		
CV_4	- 0.01	0.00	0.03	0.03	0.01	1.00	
CV_5	- 0.07	- 0.03	0.02	0.05	- 0.05	0.01	1.00

Appendix 4: Test for the distribution assumption of retrieving time in the retrieval model

Dependent variable: Retrieval time per palette	**Weibull**	**Tobit**	**Logistic**	**Log-normal**	**Log-logistic**
Storage system (**IV**)	0.3426*** (0.0064)	59.5147*** (0.9608)	59.2009*** (0.9476)	0.3914*** (0.0072)	0.3849*** (0.0068)
Volume per palette	0.0029*** (0.0001)	0.3998*** (0.0062)	0.5084*** (0.0083)	0.0028*** (0.00005)	0.0036*** (0.0001)
SKU on palette	0.0160*** (0.0006)	2.8675*** (0.0935)	2.7698*** (0.0866)	0.0238*** (0.0007)	0.0218*** (0.0007)
Travel distance	-0.0005*** (0.00004)	-0.0817*** (0.0067)	-0.0841*** (0.0080)	-0.0006*** (0.0001)	-0.0007*** (0.0001)
Storage height	-0.0001*** (0.000004)	-0.0090*** (0.0006)	-0.0090*** (0.0006)	-0.0001*** (0.000005)	-0.0001*** (0.000005)
Forklift operator experience	-0.00001*** (0.000001)	-0.0014*** (0.0002)	-0.0014*** (0.0001)	-0.00001*** (0.000001)	-0.00001*** (0.000001)
Operator fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	4.9580*** (0.0054)	120.9959*** (0.8126)	112.9810*** (0.7610)	4.7080*** (0.0061)	4.7158*** (0.0060)
Observations	98,625		98,625	98,625	98,625
Forklift operator	31	31	31	31	31
AIC	1,108,801	1,127,140	1,120,972	1,106,186	1,105,579
BIC	1,109,162	1,127,501	1,121,333	1,106,547	1,105,940
LL	-554,362	-563,532	-560,448	-553,055	-552,751
chi^2 (df = 6)	8,075.8220***	10,011.5400***	11,110.7800***	8,787.5630***	9,656.3380***

Note: Robust standard errors in parentheses; 192 order pickers included; *p < 0.05; **p < 0.01; ***p < 0.001. Lowest AIC and BIC and best LL for log-logistic AFTM.