mathematics

Article

Integrated Order Picking and Multi-Skilled Picker Scheduling in Omni-Channel Retail Stores

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Abstract: Utilizing local brick-and-mortar stores for same-day order fulfillment is becoming prominent in omni-channel retailing. Efficient in-store order picking is critical to providing timely value-added omni-channel delivery services. Despite numerous studies on order picking in traditional logistics warehouses and distribution centers, there is scant research focusing on in-store order fulfillment with the multi-skilled workforce in omni-channel retail stores. We studied the integrated Order Picking and Heterogeneous Picker Scheduling Problem (OPPSP-Het) in omni-channel retail stores. We characterized the OPPSP-Het in a mixed-integer linear optimization model with the objective of the minimization of total tardiness of all customer orders. A hybrid heuristic combining the genetic algorithm and variable neighborhood descent was designed to obtain effective solutions. Extensive experiments were conducted to validate the performance of the proposed approach relative to existing algorithms in recent literature. We further numerically showed the effects of order size and heterogeneous workforce on order fulfillment performance. We lastly emphasized the importance of workforce flexibility as a cost-effective approach to improving in-store order fulfillment performance.

Keywords: multi-skilled workforce; order picking; omni-channel retail stores; workforce flexibility; heuristic algorithm

MSC: 68M20

Citation: Mou, S. Integrated Order Picking and Multi-Skilled Picker Scheduling in Omni-Channel Retail Stores. *Mathematics* **2022**, *10*, 1484. https://doi.org/10.3390/math10091484

Academic Editor: Ripon Kumar Chakrabortty

Received: 9 March 2022
Accepted: 25 April 2022
Published: 29 April 2022

1. Introduction

Utilizing local retail establishments to provide same-day omni-channel delivery service has become more and more popular in recent years. Compared with traditional e-commerce logistics, it is more convenient to reach neighborhood customers under the Buy Online and Pickup in-Store (BOPS) and "ship-from-store" modes [1,2]. For example, it has been an essential service guarantee for major players in the same-day e-commerce delivery industry, such as Meituan and Hema, to provide a 30 min grocery delivery service to consumers within three kilometers of a neighborhood store. Furthermore, these omni-channel shopping habits have flourished during the period of the pandemic outbreak, which dramatically restricts the mobility of customers for visiting local brick-and-mortar retail stores to purchase grocery and daily use products.

These rapid changes in the same-day delivery service pose great pressure on efficient in-store order fulfillment and intra-city delivery [3]. Because it is common to outsource vehicle delivery services to major O2O platforms, such as Meituan in China and Instacart in the United States, some omni-channel retailers concentrate mainly on improving the efficiency of in-store order fulfillment to reduce the total tardiness of customer orders. A delay in order fulfillment may lead to large penalties in customer retention and loyalty in the competitive market.

In addition, the multi-skilled workforce that is widely observed in retail practice has been less concerned in academia until recent years [4–6]. In the setting of traditional logistics warehouses, workforce heterogeneity may not be prominent because specialized pickers are the majority of the entire workforce. However, full-time, part-time, and temporary stores associates who may have various skillsets are commonly deployed in retail stores. Moreover, in omni-channel retail stores, deploying a group of specialized pickers may be a huge cost burden for retailers who are in the transition stage toward omni-channel retailing.

To the best of our knowledge, the problems of jointed batching orders and allocating batch sequences for the multi-skilled workforce in omni-channel retail stores have not been addressed in the literature. If the pickers are heterogeneous, the processing time for a customer order will highly depend on the assigned picker. In traditional order batching and sequencing decisions, the complexity of assigning m groups of order batches to a team of p different pickers will increase by a factor of $\mathrm{P}(p, m)$. Thus, sophisticated solution methods are necessary to obtain satisfying batch schedules and picker allocation in reasonable computational time.

Based on discussions with retail practitioners, this study establishes a mixed-integer linear optimization model for the integrated Order Picking and Heterogeneous Picker Scheduling Problem (OPPSP-Het) with the objective of minimizing the total tardiness. OPPSP-Het comprises interactive decisions on order batching, batch sequencing, and picker allocation decisions. An effective heuristic that combines the genetic algorithm (GA) and variable neighborhood descent (VND) is then proposed to resolve large-size instances. The effectiveness of the proposed solution is validated against heuristics in recent literature, using extensive computational experiments. Moreover, the superiority of the proposed method over other heuristics holds across various order sizes and workforce compositions. The results also suggest that allocating the multi-skilled workforce can yield almost the same performance as deploying the same number of specialized pickers, leading to less investment in hiring specialized pickers in retail stores.

Overall, this research highlights the essence of taking into account workforce heterogeneity in order picking. The contributions of this study are two-fold. First, we address a practical problem that is addressed less in the previous literature. Workforce heterogeneity is explicitly incorporated in order picking and picker scheduling problems in omni-channel retail stores. Second, we designed a hybrid heuristic that utilizes the advantages of population-based and single-point search algorithms to effectively and efficiently resolve the mathematical model in which the computational complexity is incurred due to heterogeneous skillsets. The results of extensive experiments validate the performance of the proposed solution approach and suggest that dynamically allocating a flexible workforce on the sales floor may be a cost-effect approach to guaranteeing timely order fulfillment service in omni-channel retail stores.

The remainder of this study is organized as follows. We review the related literature and provide the position of this study in Section 2. Section 3 presents the mathematical model for the integrated order picking and heterogeneous picker scheduling problem. We, in Section 4, present a novel hybrid heuristic to provide high-quality solutions. Section 5 presents extensive computational experiments. We conclude this research and highlight future research in Section 6.

2. Literature Review

Order picking has been long acknowledged as the most labor-intensive operation in traditional warehouses. Extensive operational research studies are produced to improve order fulfillment efficiency [7,8]. Although various operational differences between traditional logistics warehouses and omni-channel retail stores, reviewing articles that address integrated order picking decisions in manual picker-to-parts warehouse helps facilitate the progress of this study. Since there are recent overview studies on warehouse operations in the e-commerce era [9], efficient order picking system design [10], human factors in order picking [6], and warehousing systems for brick-and-mortar retail chains [11], we rather reviewed closely the relevant studies published after 2010 except for seminal research providing a comprehensive summary in this broad field.

To the best of our knowledge, Henn and Schmid [12] were the first to investigate the joint order batching and batch sequencing problem with the objective of minimization of the total tardiness. The authors explored various metaheuristics to resolve the problem of a single picker. Menéndez et al. [13] further investigated the joint order batching and batch sequencing of a single picker under other routing strategies and proposed a general variable neighborhood search (GVNS) algorithm to efficiently resolve the problem. Chen et al. [14] proposed a non-linear mixed-integer programming approach on order batching, batching sequencing, and order routing of a single picker so as to minimize the total tardiness. The GA was applied to solve the order batching and batch sequencing problem in which a nested ant colony optimization (ACO) heuristic was applied to determine the optimal picker route.

Henn [15], which is the closest to our research, firstly proposed VND and variable neighborhood search (VNS) heuristics to address the joint order batching and sequencing decisions for multiple homogeneous pickers. The extensive computational experiments indicate that the deterministic VND algorithm outperforms a stochastic VNS approach. Scholz et al. [16] introduced a VND algorithm for the integrated order batching, batching assignment, and sequencing as well as picking routing problems. van Gils et al. [17] proposed an Iterated Local Search (ILS) algorithm to address the integrated order batching, routing, and sequencing problem with the objective of minimizing the total order pick time. A real-life case evidenced the substantial performance benefits gained from integrating batching, routing, and picker scheduling. Ardjmand et al. [18] specifically aimed to minimize the makespan (namely the maximum throughput time for a picker) of the order assignment, order batching, and picker routing problem in a wave picking warehouse. They proposed a Lagrangian decomposition heuristic combined with particle swarm optimization algorithm for small-sized waves and a hybrid parallel simulated annealing and ant colony optimization (PSA-ACO) to solve large-scale problems. Numerical experiments suggest that the increase of workforce size (or picking capacity) significantly reduces makespan in the setting of a high ratio of order to workforce size (or picking capacity). Muter and Öncan [19] presented a bi-objective order picking and picker schedule problem in which both makespan and total tardiness were minimized. The authors propose a column generation-based exact algorithm. Rasmi et al. [20] specifically focused on the wave picking systems in which mixed-storage policy is applied and proposed the Decomposition of Order Picking into order Batching, batch Assignment, and picker Routing subproblems (DOPBAR) to resolve the problem. Furthermore, the authors examined the trade-offs between makespan and labor cost. Žulj et al. [21] studied autonomous mobile robots (AMRs)-assisted picker-to-parts systems in which the warehouse is partitioned into disjointed zones and proposed an efficient heuristic solution approach. However, none of the aforementioned literature explicitly considers a heterogeneous workforce.

The e-commerce retailing environment brings a variety of challenges for practitioners with a growing trend of small-sized customer orders, large SKU variety, limited storage space, and tight delivery schedules [9,22]. The prevalence of omni-channel retailing revitalizes physical brick-and-mortar stores [2]. There is an increasing number of studies that specifically focus on omni-channel retail stores. Due to the strict requirements of on-time same-day delivery, some researchers jointly optimize in-store order picking and vehicle deliveries. Schubert et al. [23] evaluated the benefits of integrating order picking and vehicle delivery, using extensive numerical experiments for simulated data and real-life data, which account for approximately 13% total cost saving on average compared to a sequential procedure, which is typically applied in retail practice. Zhang et al. [24] studied an online scheduling problem for in-store order batches and deliveries and validated the performance of several rule-based solutions. Furthermore, more factors are incorporated in the jointed in-store order picking and delivery problem [25], such as multi-zone [26] and the constraint on food and non-food category products [27].

Despite the fact that order picking has been long recognized as labor-intensive in manual warehouses, heterogeneous workers only are considered until recent studies [6].

Grosse et al. [28] provided a framework for incorporating human factors, namely perceptual, mental, and physical aspects, in various stages of order picking processes. Among these aspects, the learning curve, which is the nature of repetitive manual work, is one of the most commonly incorporated factors in reflecting skill heterogeneity [29]. Grosse and Glock [30] presented an approach to model workers learning, and the results of their numerical experiments suggest that considering the learning effect would result in better predictability of throughput times of customer orders and relevant to worker allocations. Zhang et al. [31] detailed the impact of order pickers' learning effect on the online-to-offline order picking and vehicle delivery problem and provided the optimal assignments between batches and order pickers with learning heterogeneity. In contrast with explicit modeling workforce heterogeneity, Matusiak et al. [32] estimated the skill proficiency of each picker based on historical performance data and then established a batching and generalized assignment problem with a heterogeneous workforce. Experiment results suggested an almost 10% improvement in order fulfillment time thanks to the consideration of skill differences.

We summarized the related literature from the perspectives of the number of pickers, workforce heterogeneity, the operational environment, objectives, and solution approaches, as shown in Table 1. The summary suggests that the integrated order picking and heterogeneous picker scheduling problem in omni-channel retail stores has yet not been addressed. In this study, we specifically consider the heterogeneous skill in the jointed order batching, batch sequencing, and picker allocation decisions and propose a novel hybrid GAVNS heuristic to generate near-to-optimal solutions.

Table 1. Summary of related articles.

Study	Multiple Picker	Setting	Objective	Solution
[12]	A picker	Warehouses	Tardiness	ILS, ABHC
[13]	A picker	Warehouse	Tardiness	GVNS
[14]	A picker	Warehouses	Tardiness	GA-ACO
[15]	Homogeneous	Warehouse	Tardiness	VND, VNS
[16]	Homogeneous	Warehouse	Tardiness	VND, VNS
[17]	Homogeneous	Warehouse	Order pick time	ILS
[18]	Homogeneous	Warehouse	makespan	LD-PSO, PSA-ACO
[19]	Homogeneous	Warehouse	Travel time and makespan	Column generation-based exact algorithm
[20]	Homogeneous	Mixed-shelves	Makespan, labor cost	DOPBAR
[21]	Homogeneous	AMRs-assisted picker-to-parts system	Tardiness	ALNS/NEH
This study	Heterogeneous	Omni-channel retail stores	Tardiness	GAVNS

3. Omni-channel Order Picking Model

3.1. Problem Definition

The schematic layout of an omni-channel retail store, which is in line with previous studies [31,33], is illustrated in Figure 1. Shelf layout and storage assignment are given and are irrelevant to this research. A number of online customer orders with different due times within a time window are ready for order picking. There are a fixed number of specialized pickers and some cross-trained employees available for assignment. Order information and workforce skills are assumed a priori. The purpose of this research is to (near-to) optimally address the integrated order batching, batch sequencing, and picker scheduling problem so that to minimize the total tardiness.

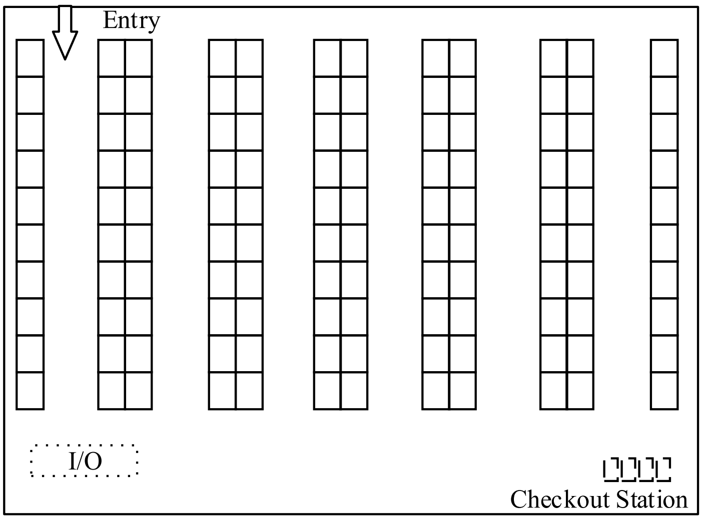

Figure 1. Retail store layout.

The process of in-store order fulfillment, similar to what is performed in traditional warehouses, constitutes the following sub-activities, namely

- Setup time for any administrative and preparation tasks;
- Travel time that a worker spends walking around shelves, and it is subject to a picking route;
- Search time for identifying and positioning items that needed to be picked;
- Pick time that a worker retrieves items from the picking position; and
- Pack time for packaging and labeling orders.

Note that we explicitly consider the factor of search time in OPPSP-Het. The skill difference of store associates in search time is characterized by utilizing a learning curve framework [28,30].

3.2. Assumptions and Notations

In line with the practice of the partner retailer, we establish the following assumptions:

- All customer orders need to be grouped into batches, and order split is prohibited.
- Setup time and pack time are assumed constant and ignored because these two factors are correlated with the number of customer orders.
- The workforce is heterogeneous in terms of picking efficiency in search time, which is highly correlated with the familiarness of each worker with the specific storage location.
- Pick time is associated with the total quantity of items picked in a batch. We assume that pickers' skill proficiency, type of SKU, and shelf layer do not affect the unit pick time.
- A dedicated storage policy is applied. Although some promotional commodities may be additionally displayed in the end-of-aisle (end-cap) areas [34,35], our partner retailer confirms that in most cases, pickers are required to retrieve items, if applicable, from dedicated shelves rather than end-of-aisle areas.
- There is no shortage of commodities on shelves in the retail stores.
- Shelf width in retail stores is assumed wide enough so that the impact of congestion is neglected or minor.

The notation of variables used in the mathematical models is presented in Table 2.

Table 2. Notations.

Parameter	Explanation
O	The set of customer orders, indexed by i and j;
M	The set of SKUs, indexed by m;
P	The set of pickers, indexed by p;
B	The sets of order batches, indexed by b;
Q	The maximum quantity of orders in one batch;
q_{im}	The quantity of commodity m within order i;
t_1	Time for the picker to check and pick per commodity;
t_2	Time for the picker to search for an SKU for the first time;
t_2^p	Time for picker p to search for an SKU;
v	Average walking speed during the picking process;
T_i^t	Tardiness of order i;
T^t	The cumulated tardiness time;
T_i^u	Due time for order i;
T_{pk}^c	The completion time of the batch picked by p at position k;
T_i^f	Total fulfillment time for completion of batch b;
T_{pk}^f	Total fulfillment time for the batch picked by p at position k;
Θ	A sufficiently large positive number;
d_1	Width of a picking face;
d_2	Depth of a picking face;
L	The length of the parallel aisle;
w	Width of an aisle;
w_b	The number of aisles visited in batch b;
X_{ib}	$X_{ib} = 1$ if customer order i is assigned to batch b. Otherwise, $X_{ib} = 0$;
G	Vector $G = (g_y, g_a)$ concerns the order in the furthest aisle in batch b, in which g_y is the column coordinate, and g_a is the index of the aisle;
P_b	$P_b = 1$ if the number of aisles visited in batch b is odd;
D_b	The total travel distance for batch b;
ψ_{im}	$\psi_{ib} = 1$ if order i contains commodity m. Otherwise, $\psi_{im} = 0$;
Y_{bpk}	$Y_{bpk} = 1$ if batch b is assigned to picker p at the position k. Otherwise, $Y_{bpk} = 0$.

3.3. Mathematical Model

The objective of OPPSP-Het is to minimize the total tardiness so as to assume a timely order fulfillment as well as the coordination with vehicle delivery [36]. The mixed-integer linear programming model is formulated as below:

$$\text{Minimize } T^t \tag{1}$$

Subject to

$$\sum\nolimits_{b\in B} X_{ib} = 1 \tag{2}$$

$$\sum\nolimits_{i\in b} \sum\nolimits_{m\in M} q_{im} X_{ib} \le Q \tag{3}$$

$$T^t = \sum\nolimits_{i\in O} T_i^t \tag{4}$$

$$D_b = [(\omega_b - P_b)L + 2d_1 g_y P_b] + [4(g_a - 1)d_2 + 2(g_a - 1)w)] \tag{5}$$

$$T_b^f \ge t_1 \sum\nolimits_{m\in M} q_{im} X_{ib} + t_2^p \sum\nolimits_{m\in M} \psi_{im} X_{ib} + \frac{D_b}{v} \tag{6}$$

$$T_{p1}^f \le T_{p1}^c \tag{7}$$

$$T_{pk}^f + T_{p(k-1)}^c \le T_{pk}^c \tag{8}$$

$$T_{pk}^c - T_i^t - \Theta\left(1 - X_{ib} Y_{bpk}\right) \le T_i^u \tag{9}$$

$$\sum\nolimits_{b\in B} Y_{bpk} = 1 \tag{10}$$

$$\sum_{p \in P} \sum_{k \in K} Y_{bpk} = 1 \tag{11}$$

$$T^{f}_{pk} \geq 0 \tag{12}$$

$$T^{t}_{i} \geq 0 \tag{13}$$

$$X_{ib},\ \forall i \in O, \forall b \in B \text{ is a binary variable}$$

Objective Function (1) minimizes the total tardiness of order fulfillment. The tardiness of order fulfillment is characterized by the difference between completion time and due time, as shown in in Equation (9).

Constraint (2) confirms that each customer order must be assigned to a batch. Order separation is not allowed.

Constraint (3) limits the maximum cumulative order quantities within a batch.

Constraint (4) calculates the cumulative tardiness.

Constraint (5) shows the total travel distance for a batch with the assumptions of an *S*-shaped route. We assume an *S*-shaped route, which is widely applied in practice. Previous literature shows that applying heuristics rather than following the mathematically optimal routes may be easier for pickers because the optimal route may generate possible disruptions [37]. In an *S*-shaped routing strategy, a picker walks thoroughly any aisle containing items within a batch but skips the aisles with no pick task. After picking the last commodity within a batch or an order, the picker returns directly to the I/O point for further operations. We do not explore the other routing heuristics, as this study is rather focused on order batching and heterogeneous pick scheduling problem. For readers interest in other routing heuristics, Masae et al. [38] provided the most recent summary on the order routing problem.

Constraint (6) calculates the total order fulfillment time for a batch.

Constraints (7) and (8) capture the iterative sequence of a picker so as to guarantee that two batches do not overlap.

Constraint (9) calculates the tardiness of every order. Specifically, the completion time of all orders within a batch equals the latest time that all orders are completed.

Constraint (10) confirms that each batch must be assigned to a picker at a position.

Constraint (11) confirms that each batch must be performed.

Constraints (12) and (13) impose non-negativity on completion time and tardiness time.

4. Solution Design

The nature of OPPSP-Het combines order batching, batch sequencing, and picker allocation problems. The subproblem, e.g., the order batching problem that groups customer orders to minimize travel distance, has been long characterized as NP-hard and large-sized instances that cannot be solved for the optimal solutions in a reasonable time window [37,39,40]. The joint order batching and sequencing problem with a fixed-routing strategy has been proved to be an NP-hard problem [12,15]. Therefore, this study proposes a hybrid heuristic combining a genetic algorithm and variable neighborhood descent (GAVND) to resolve OPPSP-Het. As aforementioned, one of the main contributions is to adapt and apply an effective heuristic, which enjoys the benefits of population-based and single-point search algorithms. The effectiveness of the proposed heuristic is validated against several metaheuristics commonly applied in previous literature. The flowchart of the proposed GAVND is shown in Figure 2.

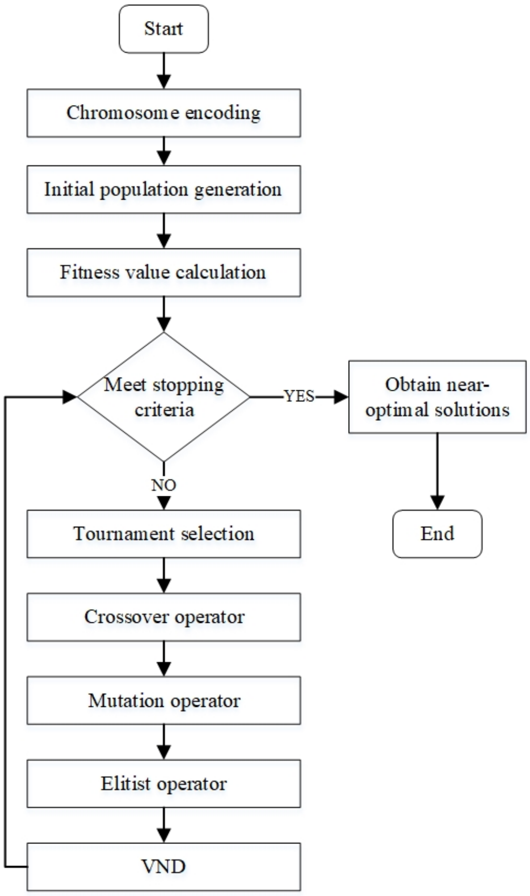

Figure 2. The flowchart of the hybrid GAVND heuristic.

In what follows, we detail the key steps in the GAVND.

- Encoding chromosome

We adopt a 2-dimensional chromosome of integers in which a genetic represents a picker-order combination. To distinguish order batches, we add a zero value at the end of each batch and place the batch sequence in a row for each picker. Figure 3 illustrates an example of how two picklists are transformed to the encoded chromosome.

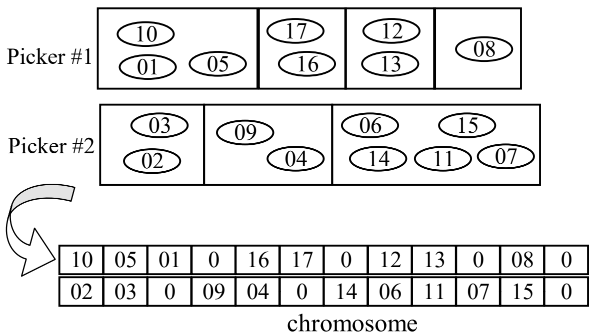

Figure 3. An example for a chromosome.

- Initial population generation

A good-quality initial chromosome population is critical to the performance of GA. Instead of purely random chromosomes, we introduce a modified earliest due date (MEDD) algorithm to generate relatively good-quality chromosomes. As shown in Algorithm 1, customer orders are randomly grouped as long as the picking capacity is not violated. The due time of each batch is updated. We then give the highest priority value to the batch with the earliest due time and assign this batch to the picker with the highest efficiency. The process continues until all batches are assigned.

- Selection, crossover, mutation, and elitist operators

A tournament selection operator is applied to produce the offspring population. Crossover and mutation operators are applied to generate variants. We utilize the neighborhood structures to carry out the crossover operator, in particular, a roulette wheel selection approach to determine which neighborhood structure to apply. The work of [15] proposed eight neighborhood structures to address the order batching and batch sequencing problem with identical pickers. The manipulation at the order level is shown below:

(a) Ω^{osh1}: Move a customer order to a different batch of the same picker;
(b) Ω^{osh2}: Move a customer order to a different picker;
(c) Ω^{osw1}: Exchange two orders of the same picker;
(d) Ω^{osw2}: Exchange two orders of different pickers.

The actions at the batch level are shown below:

(e) Ω^{bsh1}: Move a batch to a different position in the batch sequence of the same picker;
(f) Ω^{bsh2}: Move a batch to a position in the batch sequence of a different picker;
(g) Ω^{bsw1}: Exchange two batches of the same picker;
(h) Ω^{bsw2}: Exchange two batches of different pickers.

Besides the eight neighborhood structures, we consider another neighborhood structure, Ω^{psw}, in which the entire picklists are swapped between two heterogeneous pickers.

(i) Ω^{psw}: Exchange two pick lists of different pickers (picker swap).

As aforementioned, assigning m groups of order batches to identical pickers lead to one possible solution but yields $\mathrm{P}(p, m)$ possible solutions in the presence of p heterogeneous pickers. To enhance population diversity, we again use the MEDD algorithm to generate novel chromosomes at the stage of mutation. Note that the crossover and mutation operators are carried out only if the resulting offspring meet the capacity limitation of each picker. Lastly, we combine the offspring and parent populations, and only the elitist set based on their fitness values is permitted to produce the next generation.

- Termination condition

In a GA, a fixed number of iterations or computing time reached is commonly selected as the termination condition.

By the end of each iteration, a VND algorithm is implemented to further improve the population. VND is a variant of the family of VNS methodology that is a widely used local search algorithm framework [41,42]. The VND algorithm that we apply is similar to [15]. Note that, on the basis of the sequence of neighborhood structures [15], i.e., Ω^{bsw2}, Ω^{osh1}, Ω^{osh2}, Ω^{osw1}, and Ω^{osw2}, we additionally consider Ω^{psw} as the last neighborhood structure to explore.

As shown in Algorithm 2, VND starts from an initial solution and explores the first neighborhood structure in the list. In each iteration, VND identifies the element of the current neighborhood structure with the smallest objective function value. If the solution can be improved within this neighborhood structure, VND updates the solution and then again explores the first neighborhood structure in the list. Otherwise, VND explores the next neighborhood structure until no better solution can be identified.

Algorithm 1 Modified Earliest Due Date Policy

create an empty virtual batch $b \in B$
while there are unassigned orders,
  let i be the first order randomly picked from the set of customer orders;
  if order i cannot be assigned to the current batch b, **then**
    create another empty virtual batch $b = b + 1$
  end if
  $X_{ib} = 1$;
  increase batch size by adding order quantity $\sum\limits_{m \in M} q_{im} X_{ib}$
end while
calculate the due time for each batch $b \in B$;
sort ascendingly the set of batches according to due dates;
sort the set of pickers according to skill proficiency in the descending order;
let ζ be the pointer which indicates the first picker of the picker set;
for all batches $b \in B$
  assign the current batch to the ζ picker;
  let ζ indicate the next picker, and reset $\zeta = 1$ if all pickers have been pointed;
end for

Algorithm 2 Variable Neighborhood Descent

Input: neighborhood structures $\Omega_\varrho, \varrho = 1, \ldots, \varrho^{\max}$, the initial solution s_0
let $\varrho = 1$ be the point related to the first neighborhood structure in the list;
while $\varrho \leq \varrho^{\max}$
    $s^* = \operatorname*{argmin}_{p \in P} T(s) | s \in \Omega_\varrho$
    if $T(s^*) < T(s_0)$ **then**
        $s_0 = s^*$;
        $\varrho = 1$;
    else
        $\varrho = \varrho + 1$;
    end if
end while

5. Computational Experiments

We build this computational case on the basis of an omni-channel supermarket that we collaborated with. This representative supermarket has a rectangular store layout in which the I/O station is located at the bottom-left corner, and aisle #1 is the leftmost aisle (see Figure 1). The parameter values of the case store are summarized in Table 3.

Table 3. Experiment parameters.

Parameters	Values
Number of picking faces in an aisle	40
Number of picking aisles	10
Walking speed	40 m/min
Width of a picking face d_1	2 m
Aisle length L	20 m
Depth of a picking face d_2	2 m
Picking capacity Q	20
Due time	$U(10, 25)$
Retrieval speed t_1	0.16 min/item
Base search time per pick face	1 min/SKU
Learning rate	0.95
Pick experience parameter	100 or 1000

5.1. Experimental Data Setup

The store has 20 parallel racks (equivalently 10 picking aisles) and 10 picking columns per rack. Instead of demand at the item level, we rather focus on category-level demand, equivalently on average 10 SKUs at each pick column and 10 pick columns per rack. The total number of SKUs equals 2000, conforming with the assortment size in a typical grocery store. The length of a picking face, d_1; the associated depth, d_2; and the aisle width, w, are 2 m. The length of a parallel aisle, L, is 20 m.

The demand of items per picking column/face is assumed to follow a negative binomial distribution, which is denoted by (r, p) [3,34]. The probability of success p for items within Classes A, B, and C are set as 0.96, 0.975, and 0.99, respectively. Let $r = 1$, and the average order size, $np(1-p)$, ranging between 1.98 and 7.68, conforms to empirical observations and previous case studies [33]. The maximum picking capacity is 20 items per basket. Notably, the largest order size should not be great than the basket capacity, as we assume no order split is permitted.

Furthermore, omni-channel grocery delivery service tends to provide a 30 min service guarantee. Given the various distance between the store and neighborhood consumers, we assume vehicle delivery time varies between 5 min and 20 min. Thus, the due time for order picking is thus assumed uniformly distributed $U(10, 25)$.

Unlike storage assignment decisions in a traditional logistics warehouse, the random storage assignment policy that is commonly tested in previous literature is rarely observed in retail stores [2]. We mimic the arrangement of ABC classes, in which the percentages of the number of storage spaces for each class are expressed as 10%:20%:70%. Because shelves in brick-and-mortar retail stores are typically arranged to prolong in-store customer shopping trips so as to increase the likelihood of pulse purchases [43,44], items in classes A, B, and C are placed from the rightmost aisles to the leftmost aisles.

The entire workforce available for omni-channel order fulfillment comprises specialized pickers and flexible store associates, such as checkout cashiers and salespersons, who are not trained or hired for in-store order picking but are capable of order picking. The number of specialized pickers available is three, which also serves as the benchmark in the computational experiments. The proficiency of flexible store associates in order picking varies in search time. We utilize the framework of a learning curve, as shown in (14), to characterize the individual proficiency in order picking. t_2 denotes the initial search time for beginners. LR_p indicates the learning rate of individual difference in search time, and κ is the cumulated item picked previously. We let $LR_p = 0.95$ and $t_2 = 1$ to control systematic variance but manipulate the value of κ to differentiate individual skills. We set κ as 100 and 1000, indicating the specialists' and the flexible workers' proficiency. We note that differentiating individual proficiency in order picking is the sole purpose of applying this learning curve formula, and we have no intention to justify a specific learning curve formula.

$$t_2^p = t_2 \kappa^{lgLR_p/lg2} \tag{14}$$

Workforce composition is one of the significant characteristics that distinguish order fulfillment in retail stores from that in traditional warehouses. Besides the base workforce (i.e., three specialized order pickers), we additional consider six workforce compositions. As shown in Table 4, we incrementally add more flexible or specialized workers to analyze the benefits of a heterogeneous workforce in order fulfillment. Furthermore, we randomly generate 40, 60, and 80 customer orders in the experiment. Test instances and results are deposited in the Harvard Dataverse repository (https://doi.org/10.7910/DVN/HZI7CV). There are 10 replications for each group.

Table 4. Experiment Design.

Factor	Factor Levels
Workforce Configuration	(0) 3 specialists (Base); (1) 3 specialists and 1 flexible worker (Base + 1F); (2) 4 specialists (Base + 1S); (3) 3 specialists and 2 flexible workers (Base + 2F); (4) 5 specialists (Base + 2S); (5) 3 specialists and 3 flexible workers (Base + 3F); (6) 6 specialists (Base + 3S).
Online Orders	(1) order size $\|O\| = 40$; (2) order size $\|O\| = 60$; (3) order size $\|O\| = 80$.

We set retrieve time, t_1, as constant and homogeneous for items located on different layers of a picking column. The walking speed of each picker is 40 m/min.

Policies for order picking and picker scheduling define how customer orders are batched, sequenced, and allocated. The Earliest Start Date (ESD) rule that is also implemented by Henn [15] and Scholz et al. [16] is applied as the baseline for comparison. As shown in Algorithm 3, this priority-based algorithm firstly assigns a priority value for each customer order based on its due date in the ascending order. Two kinds of feasible picking positions are identified if (1) the current picking capacity is large enough for the selected customer order, or (2) a new picking position is created. Note that when the algorithm calculates the completion time of a picking position, the heterogeneous picking efficiency of a picker has been explicitly applied. Lastly, the algorithm assigns online customer orders iteratively to any feasible picking position that has the earliest start date.

Algorithm 3 **Earliest Start Date Policy**

sort ascendingly the set of customer orders according to due dates
while there are unassigned orders,
  let j be the first order in the sorted list;
  for all order pickers, $p \in P$
    if j can be assigned to the last batch of picker p, **then**
      sd_p = start time of the last batch of picker p (CASE 1);
    else
      sd_p = completion time of the last batch of picker p (CASE 2);
    end if
  end for
  $p^* = \operatorname*{argmin}_{p \in P} sd_p$;
  assign j to the last batch of picker p^* (CASE 1), or open a new batch for picker p^* and assign j to it (CASE 2);
  remove j from the list of unassigned orders;
end while

As an NP-hard problem, previous literature has shown that for instances with more than 20 orders, the commercial solver, such as CPLEX, cannot report a solution with a CPU time limit of several hours [18,19]. Hence, for the sake of brevity, this study only reports the effectiveness of GAVND compared with several classic heuristics reported in recent studies. Besides GAVND, we additionally consider an elitist-based GA policy and a VND algorithm.

- The elitist-based GA policy is obtained by running GAVND except for the part of the VND operator.
- The VND algorithm is implemented by firstly obtaining the initial solution based on the ESD rule and then running Algorithm 2.

To compare policy performance, we calculate the relative gap between two policies in terms of their tardiness values for each of the 210 instances. As shown below, Gap_{ESD}^{VND}, Gap_{ESD}^{GA}, and Gap_{ESD}^{GAVND} denote the performance of VND, GA, and the proposed GAVND policies, relative to the ESD rule, which also serves as the benchmark in previous literature [15,16].

$$Gap_{ESD}^{VND} = \left(T_{ESD}^{t} - T_{VND}^{t}\right)/T_{ESD}^{t} \tag{15}$$

$$Gap_{ESD}^{GA} = \left(T_{ESD}^{t} - T_{GA}^{t}\right)/T_{ESD}^{t} \tag{16}$$

$$Gap_{ESD}^{GAVND} = \left(T_{ESD}^{t} - T_{GAVND}^{t}\right)/T_{ESD}^{t} \tag{17}$$

Moreover, we need to verify the performance of the proposed GAVND policy relative to the other two heuristics. As shown below, Gap_{VND}^{GAVND} and Gap_{GA}^{GAVND} indicate the performance of the proposed GAVND policy relative to the VND and GA policies.

$$Gap_{VND}^{GAVND} = \left(T_{VND}^{t} - T_{GAVND}^{t}\right)/T_{VND}^{t} \tag{18}$$

$$Gap_{GA}^{GAVND} = \left(T_{GA}^{t} - T_{GAVND}^{t}\right)/T_{GA}^{t} \tag{19}$$

We run numerous pre-test trials to find the best parameters for the hybrid GAVND algorithm. The algorithm parameter is determined so that the GAVND reaches steady states to obtain promising solutions within acceptable computing time, i.e., five minutes. We set the crossover and mutation rates to 0.5 and 0.2. The size of the initial population is 10, and there are 50 iterations. The GAVND and the other heuristics are coded in MATLAB R2021a and run on a computer with the 11th-Gen Intel(R) Core(TM) i7-1165G7 @2.8 GHz, 8 GB RAM, under Microsoft Windows 10 operating system.

5.2. Computational Study Results

We run computational tests to compare the performance of three heuristics with the benchmark policy applied in previous studies [15,16], as shown in Figure 4. All solutions generated by the three heuristics outperform those yielded by the ESD rule, evidenced by the positive average gap values. For each group characterized by order size and workforce configuration, GAVND yields the best performance, followed by GA and VND. The average gap between GAVND and the ESD rule, Gap_{ESD}^{GAVND}, exceeds 10% in all groups. It thus can be concluded that GAVND can generate considerably good quality solutions for various order sizes and workforce configurations.

Besides the illustrative description in Figure 4, we are further interested in the effectiveness of the proposed GAVND compared with VND, GA, and ESD policies. We ran statistics check using IBM SPSS Statistics 22. Significance values in the Kolmogorov–Smirnov test and Levene's test are less than 0.05, violating the assumptions of the *t*-test. (Detailed reports for checking assumptions are intentionally omitted in the research due to page limit but available from the corresponding author). Thus, the Wilcoxon rank-sum test is applied to verify whether the proposed GAVND outperforms VND, GA, and ESD policies. The results of the Wilcoxon rank-sum test are shown in Tables 5 and 6. Note that a sample with zero values, denoted as 0 in the column of Group in Table 5, is created to construct two samples for the Wilcoxon rank-sum test. The sample with calculated gap values per instance is denoted as 1 in the column of Group in Table 5. The two-sided *p*-values from asymptotic 2-tailed are 0.000, suggesting the median value of Gap_{ESD}^{GAVND}, Gap_{VND}^{GAVND}, and Gap_{GA}^{GAVND} significantly deviate positively from that in the sample of zeros. It thus can be concluded that the proposed GAVND outperforms ESD, VND, and GA. Moreover, we further run the Wilcoxon rank test for groups of three order sizes and groups of seven workforce configurations. The superiority of the proposed GAVDN holds as well.

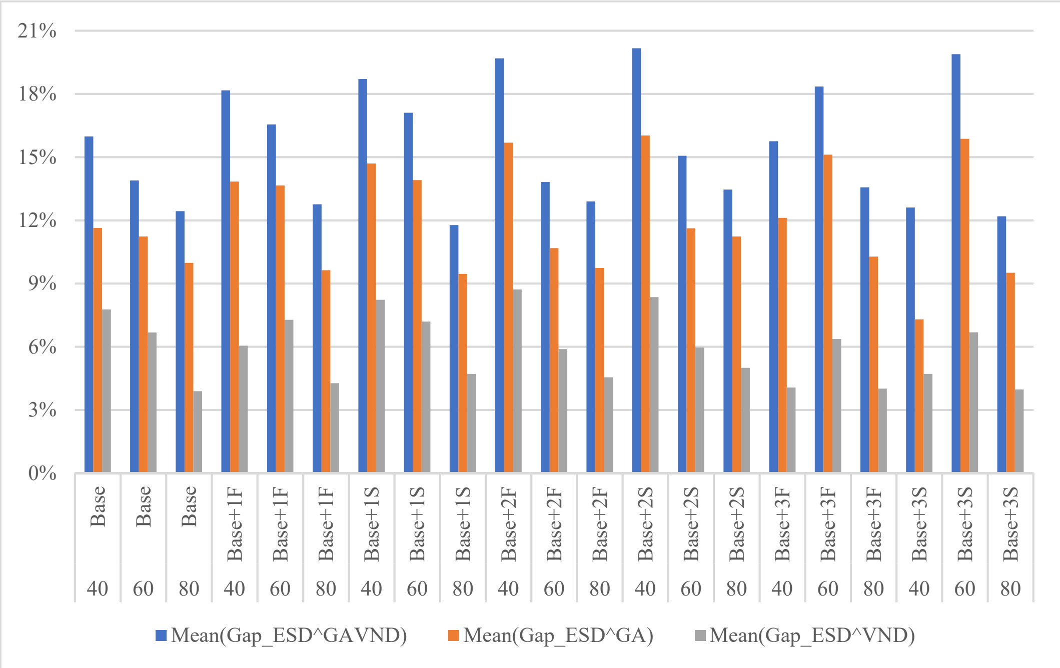

Figure 4. Performance of various heuristics.

Table 5. Rank in the Wilcoxon rank-sum test.

Performance	Group	N	Mean Rank	Sum of Ranks
Gap_{ESD}^{GAVND}	0	210	107.50	22,575.00
	1	210	313.50	65,835.00
	Total	420		
Gap_{VND}^{GAVND}	0	210	114.50	24,045.00
	1	210	306.50	64,365.00
	Total	420		
Gap_{GA}^{GAVND}	0	210	106.50	22,365.00
	1	210	314.50	66,045.00
	Total	420		

Table 6. Test Statistics in the Wilcoxon Rank Sum Test [a].

	Gap_{ESD}^{GAVND}	Gap_{VND}^{GAVND}	Gap_{GA}^{GAVND}
Mann–Whitney U	420.000	1890.000	210.000
Wilcoxon W	22,575.000	24,045.000	22,365.000
Z	−18.590	−17.327	−18.771
Asymp. Sig. (2-tailed)	0.000	0.000	0.000

a. Grouping Variable: Group.

In what follows, we explore the effect of order size and workforce configurations individually.

5.3. Effect of Order Size

The mean values of the total tardiness under ESD, VND, GA, and GAVND as well as the CPU time for the proposed GAVND are illustrated in Figure 5. First, with the increase in order size, the average performance of solutions generated by the four policies deteriorates significantly. This observation is in line with previous studies, such as van Gils et al. [17] and Muter and Öncan [19]. Second, for each order size, GAVND always yields the best performance, followed by GA, VND, and the ESD rule. This observation again validates the effectiveness of the proposed GAVND. Third, the CPU time of GAVND also increases in order size. Despite the increase in CPU time, GAVND is capable of generating effective solutions for up to 80 orders within six minutes in an ordinary computer. The discussions with partner retailers demonstrate the practicability of GAVND in a real-world environment.

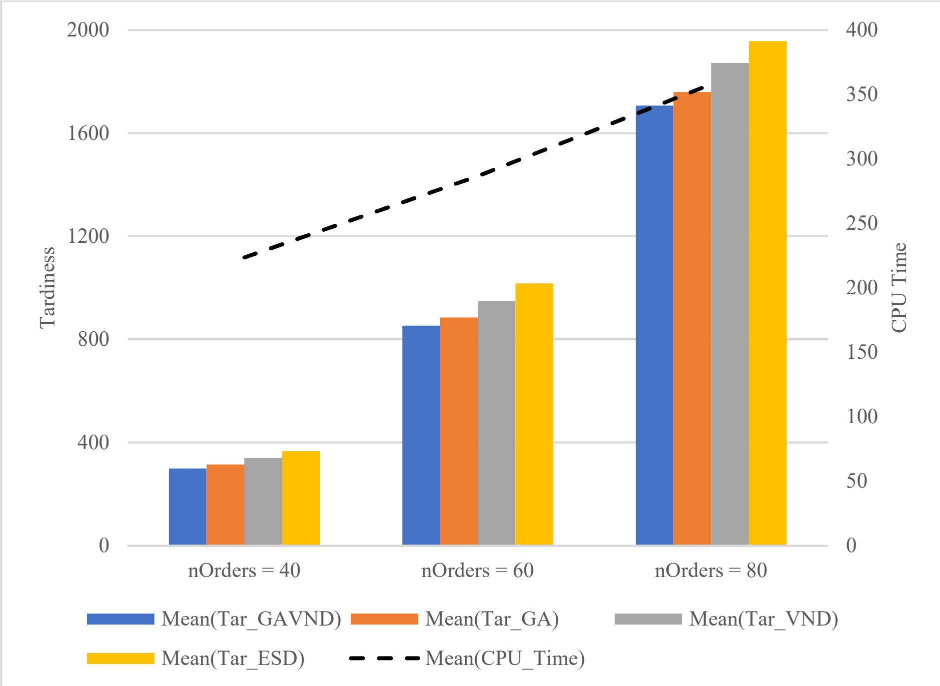

Figure 5. Effect of order sizes.

5.4. Effect of Heterogeneous Workforce

The impact of the heterogeneous workforce on the performance in order picking under the four heuristics is shown in Figure 6. Firstly, for the total tardiness at each factor level, GAVND outperforms the other three policies, suggesting the effectiveness of the proposed hybrid algorithm. Furthermore, the total tardiness decreases in the number of store associates available for order picking in omni-channel retail stores. This observation is evident because more store associates available for order picking, despite their skill proficiency, result in more parallel orders (batches) simultaneously picked in operations. However, deploying more specialized pickers to the sales floor leads to a significant increase in labor expenditure for retailing. Therefore, we are interested in the relative marginal benefits of allocating on-hand flexible store associates on the sales floor. As shown in Figure 6, the total tardiness of workforce composition (Base + 1F) is 2.66% greater than that of workforce composition (Base + 1S) under GAVND. It suggests that dynamically allocating a flexible worker for order picking from other jobs yields slightly worse operational performance than adding a specialized picker. This result suggests that the benefit of allocating a flexible worker who may be not as much as efficient as a specialized picker to complete order picking tasks can achieve almost the same effect of hiring a specialized picker. This observation is crucial to the bottom line, as cross-training store associates hired in other jobs to gain skills in order fulfillment can facilitate omni-channel order fulfillment with less fixed investment. It is thus of interest to explore effective on-site labor allocation policies in omni-channel retail stores [33,45]. Lastly, the performance difference between workforces with the same size but different skillsets (i.e., Base + 1S vs. Base + 1F, Base + 2S vs. Base + 2F, and Base + 3S vs. Base + 3F) increases in the number of flexible workers. This observation highlights that ignoring the difference in individual skills among workers may not be applicable for omni-channel retail stores where workforce heterogeneity is commonly observed.

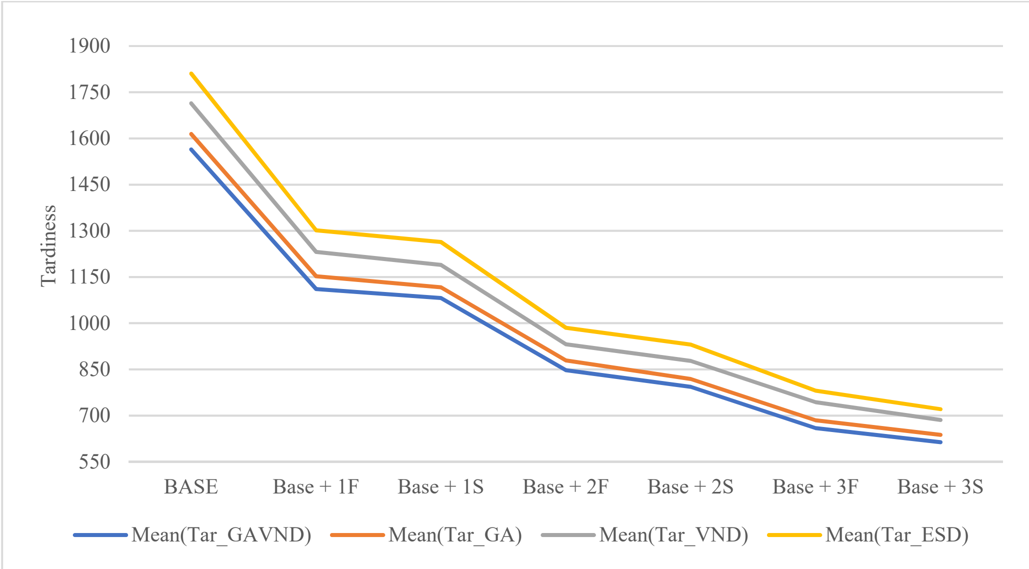

Figure 6. Effect of the heterogeneous workforce.

5.5. Discussions and Managerial Insights

In this paper, we have characterized a practice-oriented problem, namely the integrated order picking and heterogeneous picker scheduling problem in omni-channel retail stores. To the best of our knowledge, the jointed problem of order batching, sequencing, and allocating a multi-skilled workforce is not yet addressed in the literature. Previous studies oftentimes assume a homogeneous workforce, which is commonly observed in warehouse operations, but this assumption is widely challenged in retail store operations. As shown in Table 1, this study is the first to investigate the effect of a heterogeneous workforce on the classic order picking problem. Furthermore, the proposed GAVND is verified to be effective compared with benchmark heuristic in recent articles, such as Henn [15] and Scholz et al. [16], and classic mate-heuristics, such as VND and GA. However, as there are no direct benchmark instances applied for both retail stores and warehouses, we do not conclude whether the proposed GAVND outperforms heuristics in the setting of warehouse operations, such as the summarized literature in Table 1 [15–19].

Moreover, the discussions on the heterogeneous workforce, which are missed in previous studies, yield some managerial insights. A workforce constituted of specialized and flexible multi-skilled employees can generate almost the same performance as that of all specialized pickers. This observation is crucial for omni-channel retail store managers. Training store associates with skillsets for order fulfillment is easy to roll out, and the store manager can then allocate these flexible cross-trained employees to help facilitate in-store order fulfillment in real time. Thus, dynamic allocation of cross-trained employees can be a cost-effective approach to guaranteeing timely omni-channel order fulfillment service. The savings because of hiring fewer specialized pickers can be utilized for other operations.

6. Conclusions

The development of omni-channel retailing places great pressure on retailers. How to better utilize brick-and-mortar retail establishments to provide timely same-day delivery service is critical to the success of the business in the competitive market. This study focuses on addressing the integrated order picking and heterogeneous picker scheduling problem. We propose a hybrid heuristic combining a genetic algorithm and variable neighborhood descent. Extensive computational experiments have shown its suitability in producing good-quality solutions, and it outperforms other existing heuristics in the literature. Some managerial insights are provided for omni-channel retail practitioners.

The contributions of this study are two-fold. First, we put forward a variant of the integrated order picking and picker scheduling problem, with specific considerations of workforce heterogeneity. Despite the prevalence of skill differences in practice, to the best of our knowledge, there are scant order picking studies considering this factor. Second, we propose an effective and efficient hybrid algorithm to solve the problem. Considering workforce heterogeneity can add extra complexity to generate solutions. The computational experiments produce evidence of the effectiveness of the proposed GAVND algorithm. The effects of order size and heterogeneous workforce on order fulfillment performance are further discussed. Results suggest dynamic allocation of a flexible workforce may be a cost-effective approach to guaranteeing timely order fulfillment service.

This study is limited in several perspectives, and we thus expect fruitful research in the following avenues:

- Workload balancing is a typically key concern for a task allocation problem. This research can be extended to add the workload balancing measures, such as makespan and mean-based measures in the future [46], to the objective functions. Therefore, a multi-objective optimization problem can be proposed, and one may design an efficient heuristic to obtain its Pareto optimal solutions.
- The *S*-shaped routing practice is assumed in this study. Despite the prevalence in practice, we are aware that the pick route may deviate from the designed track, or walking speed may be slowed down due to the presence of offline customers in retail stores. A promising future research perspective may be designing efficient order picking systems in this complicated real-life operational environment. For example, one may focus on proposing a novel heuristic that takes into account possible detours in order fulfillment in retail stores.
- Better operational performance may be achieved by better-allocating personnel in various job roles, such as packing and checkout operations. It is worthwhile to investigate this dynamic labor allocation mechanism, with careful considerations of fairness among workers, task-switch time, and possible training cost. In this situation, a real-time or online version of order picking decisions may be of interest.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 72001224.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

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