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Case study article

Application of heuristic algorithms in warehouse order picking routes

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ABSTRACT

Order picking is a costly activity in warehouse operations, accounting for up to 65% of total warehouse operational costs. This study aims to improve the efficiency and productivity of the order picking process in a warehouse by applying two heuristic methods, namely the S-Shape and aisle-by-aisle approaches. Data were processed using InterActive Freight & Warehouse software, which is designed for warehousing and logistics management with interactive features that assist in optimizing order picking routes. The software employs heuristic methods, such as the S-Shape and aisle-by-aisle strategies, to reduce the distance workers travel to pick goods. The results show that the S-Shape method significantly reduces workers' travel distance compared to other methods. Thus, the application of heuristic methods in optimizing order picking routes proves effective in enhancing warehouse operational efficiency. The S-Shape method yields an average total distance traveled of 678.729 meters, while the aisle-by-aisle method results in 684.04 meters. Additionally, the S-Shape method increases line order productivity from 30 lines of orders per packing list to 84 lines of orders per packing list, with a cycle time of 45.25 seconds to complete the picking process for one line of orders.

1. Introduction

Warehouses play an important role in the supply chain as storage and distribution centers for goods before they are sent to customers. The main activities in warehouse operations include receiving goods (receiving), storage (put-away and storage), order picking, packaging (packing and sorting), and delivery (dispatch and shipping) [1]. Among these activities, order picking is the most expensive process, contributing up to 55% of total warehouse operational costs [2], [3]. The basic processes in a warehouse consist of receiving, put-away, internal replenishment, order picking, accumulating and sorting, packing, cross-docking, dispatch, and shipping. Receiving and storing can be categorized as inbound processes, while the others are considered outbound processes. In addition to these processes, there are also value-added services that are not mandatory but depend on the type of warehouse and the variety of services provided. Order picking routes are critical in warehouse operations, involving the efficient retrieval of products from storage locations. Optimizing these routes reduces labor costs and increases productivity, making them essential for effective supply chain management in picker-to-parts systems [4].

Order picking also significantly impacts customer service levels because it directly affects the speed and accuracy of order fulfillment [5]. The efficiency of order picking largely depends on the routing method used by workers to retrieve goods from storage locations and deliver them to the packaging area. The shorter the distance traveled, the lower the labor costs and the faster the order fulfillment process becomes. Therefore, optimizing picking routes is a key focus in enhancing warehouse productivity [6]. The challenges of today's warehouses include increasing efficiency and productivity while reducing overtime costs. Warehouse management generally oversees the implementation of five key activities: receiving, put-away, storage, order picking, and shipping [1]. Order picking stands out as the most expensive activity in warehousing, accounting for up to 55% of total operating costs, as shown in Table 1, making it a top priority for boosting productivity [1]. It can even reach 55% of total warehouse operating costs [7]. Order picking is also crucial because it directly affects customer service levels. This connection depends heavily on the optimization and accuracy of the order picking process. Optimization reflects how quickly and precisely an order can be retrieved [2], as well as how fast it becomes available for delivery to the customer.

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Table 1.
Distribution of order picking time

Activity	Percentage (%)
Traveling	55
Searching	15
Extracting	10
Paperwork and other activities	20

To improve order picking efficiency, various strategies have been developed, including heuristic methods such as S-Shape, aisle-by-aisle, return, largest gap, and combined [2]. Several studies have shown that these heuristic methods can significantly reduce workers' travel distance, thereby cutting picking time and boosting system throughput [7].

In order picking systems, travel time increases along with travel distance, so travel distance is often seen as the primary focus when designing and optimizing warehouses [2]. Heuristic routing methods are commonly used to minimize both the distance and travel time of picking routes.

Order picking route optimization, particularly with heuristic methods like the S-Shape and aisle-by-aisle strategies, plays a vital role in enhancing warehouse efficiency. The S-Shape method, as noted by [8], reduces travel distance by implementing systematic U-turns at the end of the last aisle, minimizing unnecessary movements within the warehouse. Similarly, a study by [9] pointed out that order picking efficiency is often affected by deviations from planned routes due to human behavioral factors.

Routing strategies directly influence distance and travel time. A well-designed routing strategy can significantly cut both. Improving the productivity of the order picking process involves selecting the right heuristic routing method to achieve the shortest time and distance. These strategies guide the picker by suggesting the route and the sequence for picking products from the pickup list. The goal of routing in a warehouse is to find the shortest path [10]. The best-known routing strategies include S-Shape, return, mid-point, largest gap, combined, optimal, aisle-by-aisle, and composite [2]. These heuristic routing methods shorten picking distances and can increase order picking productivity [10].

Optimizing order picking routes using heuristic methods, especially A-Shape and aisle-by-aisle strategies, is critical to boosting efficiency in warehouse operations. These methods focus on minimizing travel distance and time while accounting for factors like aisle width and congestion. The following sections outline the key aspects of these routing approaches. A-Shape routing uses a structured approach to navigate through aisles, optimizing paths by reducing unnecessary backtracking. It's particularly effective in parallel aisle systems, achieving an optimal gap of 1.38% to 9.21% in travel distance [11]. Aisle-by-aisle routing, on the other hand, involves systematically retrieving items from one aisle before moving to the next. This strategy can be modeled using mixed-integer programming to consider aisle configurations and access modes [12].

Furthermore, a study by [13] highlighted the ergonomic and economic benefits of a hybrid order picking system that combines human labor with automated solutions. They found that integrating Automated Guided Vehicles (AGVs) with heuristic routing methods strikes an optimal balance between human effort and automation, reducing operator fatigue and improving picking accuracy.

Most prior research discusses heuristic methods for order picking theoretically or through simulations. This research goes a step further by comparing two heuristic methods directly in real-world conditions, using interactive software. The study compares the distance traveled by workers in the current state (without a specific method) with the optimization results obtained through heuristic methods. The analysis process is conducted using interactive software that enables real-time calculation and visualization of routes. This research not only focuses on comparing travel distances but also measures the impact of the proposed method on order picking productivity, specifically the increase in the number of order lines that can be processed per working hour. It is hoped that the results of this research can provide practical recommendations for warehouse managers to improve operational efficiency by selecting the optimal order picking method.

2. Literature review

Order picking is one of the most complex and costly activities in warehouse operations, accounting for up to 55% of total operational costs [2]. Its efficiency significantly impacts warehouse productivity, order processing time, and customer satisfaction [1]. To optimize this process, researchers have developed various approaches aimed at minimizing workers' travel distance and time during order picking [7].

Order picking improvements can be viewed from four main perspectives: automation (particularly stock-to-picker systems), storage assignment policies, order batching, and order picking sequencing. By reviewing these areas, we aim to identify the most prevalent approaches to enhancing order picking efficiency [14].

A study focusing on Wholesale Fresh Produce Traders in China utilized the Genetic Algorithm and Heuristic Method to address order picking challenges. This research explored an extended version of joint order batching and scheduling optimization for manual vegetable order picking and packing lines, incorporating the effect of worker fatigue [15]. A heuristic approach was developed to minimize total completion time, and its performance was evaluated using numerical instances derived from real-world warehouse operations of a partnering B2C grocery company [15].

Another heuristic approach employed association rule mining (ARM) to group products into families based on similarities between stock-keeping units (SKUs) [16]. SKUs with higher similarities were placed closer to each other. This method was tested using data from a real distribution center in the food retail industry, demonstrating that data mining-driven layouts could significantly reduce travel distances during order picking [16].

In the context of omni-channel retail stores, the integrated Order Picking and Heterogeneous Picker Scheduling Problem (OPPSP-Het) was addressed through a mixed-integer linear optimization model. The goal was to minimize the total tardiness of customer orders [17].

For optimizing storage location assignments in a manufacturing firm's warehouse, a mathematical model was introduced to solve the nonlinear mixed integer optimization problem (NLMIP), specifically the Storage Location Assignment Problem (SLAP). Historical data from the warehouse management system (WMS) was used, with clustering and ABC analysis applied based on item picking frequency and co-picking occurrences. A greedy heuristic was also developed to solve the SLAP [18].

Routing strategies such as the S-shape/traversal strategy and the Return strategy were implemented in a study using a random storage method [19]. The average travel distance was calculated by considering components such as the distance from the depot to the first pick aisle, travel through sub-aisles, corrections for turns, cross-aisle travel, and the return distance to the depot. These components were used to determine the total average travel distance [19].

In a specific case involving a warehouse with a two-cross-aisle layout, five heuristic algorithms were developed to determine optimal pick-up routes [20]. The travel distances generated by each algorithm were compared, leading to improved warehouse efficiency by reducing pick-up travel distances [20].

The aisle-by-aisle method, which involves systematically picking items from each aisle, has proven effective in high-traffic warehouses with bottlenecks. This method ensures all items are picked without omissions, particularly beneficial for large order sizes [21]. It is especially useful in multi-aisle systems where routing complexity increases, enabling better system utilization and throughput by minimizing cycle times [22].

In a finished goods warehouse, long travel and search times during picking activities were identified as significant issues. To address this, a storage allocation strategy was proposed, utilizing an interaction frequency heuristic. This method calculated the interaction frequency and popularity of SKU pairs based on order lists, aiming to minimize picking time [23].

A classification of order picking systems by [24] highlighted that warehouses integrating heuristic routing policies with automation tend to achieve higher accuracy and lower operational costs. This finding aligns with our study, where heuristic methods demonstrated improvements in order picking speed and cost efficiency.

While heuristic methods offer substantial benefits, their effectiveness depends on specific warehouse configurations and operational constraints. Factors such as aisle traffic, storage assignments, and order characteristics can influence their performance [22], [25]. Additionally, integrating these methods with advanced technologies and mathematical models can further enhance efficiency, as evidenced by various studies proposing new models for order picking optimization [26]. By applying heuristic methods through interactive warehouse programs, it was found that heuristic routing can significantly shorten picking distances, thereby increasing order picking productivity [27]. Related research findings are summarized in Table 2.

3. Methods

The research flow begins with data collection, followed by initial data processing, which involves creating a layout of the current warehouse using interactive warehouse software. InterActive Freight & Warehouse is a software designed for warehousing and logistics management, offering interactive features that optimize order-picking routes using heuristic methods such as A-Shape and aisle-by-aisle. These methods help reduce the distance workers travel to pick goods. Developed by a warehousing company in Toronto, Ontario, it compares workers' travel distances under current conditions (where no method is applied, and picking is done based on individual preferences) with the distances generated by the proposed heuristic methods. The software can be accessed at https://www.roodbergen.com/warehouse/frames.htm?demo. All data processing in this study will also be carried out using this software.

Table 2.
Summary of related articles

Author	Method	Notes
[14]	Various methods to improve order picking activities	Review all methods to improve order picking activities
[15]	Order Batching Algorithm upon Similarity (OBAS)	Scheduling for manual vegetable order picking and packing lines.
[16]	ARM -based SLAP	Positioning items to minimize order picking time in a distribution center.
[17]	Mathematical and Hybrid Heuristic Design	Optimization in order picking in an omni-channel retail environment
[18]	ABC analysis and K-means	Optimize storage location assignment decisions in a warehouse
[19]	S Shape and Return	Reduce travel distance by comparing 2 methods: S Shape and Return
[20]	S Shape, Return, midpoint, Largest Gap, Aisle by Aisle	Improve warehouse efficiency by decreasing the pick-up travel distance
[27]	Interaction Frequency Heuristic	Decrease travel time and picking time in finish goods warehouse
[10]	S Shape, Largest Gap, Aisle by Aisle, Combine	Improve the productivity of order picking by shortening the distance

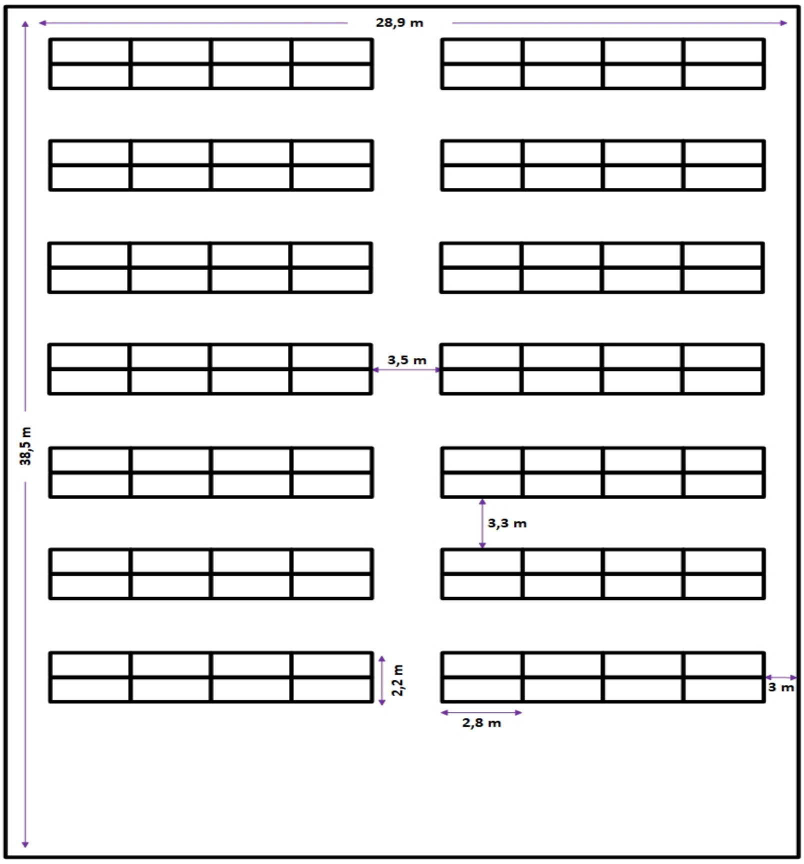

Figure 1. Warehouse layout

Table 3.
Shelf distance (meters)

Code	Distance	Code	Distance	Code	Distance	Code	Distance	Code	Distance	Code	Distance	Code	Distance
RK1	2.2	RK9	2.2	RK17	2.2	RK25	2.2	RK33	2.2	RK41	2.2	RK49	2.2
RK2	2.2	RK10	2.2	RK18	2.2	RK26	2.2	RK34	2.2	RK42	2.2	RK50	2.2
RK3	2.2	RK11	2.2	RK19	2.2	RK27	2.2	RK35	2.2	RK43	2.2	RK51	2.2
RK4	2.2	RK12	2.2	RK20	2.2	RK28	2.2	RK36	2.2	RK44	2.2	RK52	2.2
RK5	3.3	RK13	3.3	RK21	3.3	RK29	3.3	RK37	3.3	RK45	3.3	RK53	3.3
RK6	3.3	RK14	3.3	RK22	3.3	RK30	3.3	RK38	3.3	RK46	3.3	RK54	3.3
RK7	3.3	RK15	3.3	RK23	3.3	RK31	3.3	RK39	3.3	RK47	3.3	RK55	3.3
RK8	3.5	RK16	3.5	RK24	3.5	RK32	3.5	RK40	3.5	RK48	3.5	RK56	3.5

Code	Distance	Code	Distance	Code	Distance	Code	Distance	Code	Distance	Code	Distance	Code	Distance
RK57	2.8	RK65	2.8	RK73	2.8	RK81	2.8	RK89	2.8	RK97	2.8	RK105	2,8
RK58	2.2	RK66	2.2	RK74	2.2	RK82	2.2	RK90	2.2	RK98	2.2	RK106	2,2
RK59	2.2	RK67	2.2	RK75	2.2	RK83	2.2	RK91	2.2	RK99	2.2	RK107	2,2
RK60	2.2	RK68	2.2	RK76	2.2	RK84	2.2	RK92	2.2	RK100	2.2	RK108	2,2
RK61	3.3	RK69	3.3	RK77	3.3	RK85	3.3	RK93	3.3	RK101	3.3	RK109	3,3
RK62	3.3	RK70	3.3	RK78	3.3	RK86	3.3	RK94	3.3	RK102	3.3	RK110	3,3
RK63	3.3	RK71	3.3	RK79	3.3	RK87	3.3	RK95	3.3	RK103	3.3	RK111	3,3
RK64	3.5	RK72	3.5	RK80	3.5	RK88	3.5	RK96	3.5	RK104	3.5	RK112	3,5

The next stage of data processing involves calculating the distance traveled by workers to pick up all products from received orders. This calculation is performed for both the current conditions and the proposed heuristic methods. Two heuristic methods, S-shape and aisle-by-aisle, are used for this analysis. These methods are well-known, easy to understand, and provide good solutions. Additionally, they are already integrated into interactive warehouse software.

The third stage is a comparative analysis of the distances traveled by workers under the current method versus the two proposed heuristics. Currently, workers rely solely on intuition without following a structured pattern or guidance. Furthermore, an analysis of order-picking productivity will be conducted by comparing the number of order lines picked to the total picking activity in the warehouse, while also considering labor efficiency in terms of working hours.

4. Results and discussion

The distance of the storage rack from the exit is used to consider the proper storage position of each item. The summary of the distance between each shelf and the exit door in the warehouse can be seen in Table 3. Items stored in the warehouse will be sent to consumers who have placed orders. The list of goods inquiries for May 2024 can be seen in Table 4. The release time of the packing list is divided by day, indicating that several items will be shipped on each respective day.

Table 4.
Goods inquiries in May 2024

No	Code	Goods	13/05	14/05	15/05	16/05	Avg	Max Freq
1	ML01	Porcelain For En1-250a	1,500	400	1,000	100	750	3
2	ML02	Brass Stem 1-250a	1,500	400	1,000	100	750	3
3	ML03	Top Porcelain En630	350	250	500	50	287.5	3
4	ML04	Brass Stem 1-630a	350	250	500	50	287.5	3
5	ML05	Porcelain 20nf250 3shed	1,600	600	1,000	200	850	3
6	ML06	Elkom Metal Part 20nf250	1,600	600	1,000	200	850	3
7	ML07	Lv Bushing 3kv/630	110	8	50	36	51	3
8	ML08	Straight Connector	420	100	100	100	180	3
9	ML09	Plug In Bushing 24kv 250a	150	25	25	75	68.75	3
10	ML10	Tap Charger 20kv 30A 7Pos	420	20	1,000	90	382.5	3
11	ML11	Lv Bushing En1-2000A	40	16	16	20	23	3
12	ML12	Radiator Finwall	140	100	20	50	77.5	3
13	ML13	Lv Bushing En1-3150a	62	10	10	10	23	3
14	ML14	Lv Bushing 3kv/4500a	52	36	36	36	40	3
15	ML15	Lv Bushing 3kv/6500a	40	24	24	24	28	3
16	ML16	Protection Relay	18	3	3	3	6.75	3
17	ML17	Lv Bushing 10nf3150	36	8	4	8	14	3
18	ML18	Hv Bushing 52nf1000	36	8	4	8	14	3
19	ML19	Fuse Housing Bay O Nett	275	150	20	200	161.25	3
20	ML20	Connection Flag 1kv 1000a	430	300	100	500	332.5	3
21	ML21	Hv Fuse - 3011014315 Din	25	10	2	10	11.75	3
22	ML22	Hv Fuse - 301085350 Din	25	10	2	10	11.75	3
23	ML23	Gasket Cork 20nf250a	200	50	100	50	100	3
24	ML24	Hv Fuse - 300061340 Din	30	10	10	10	15	3
25	ML25	Fuse Overload	15	5	5	5	7.5	3
26	ML26	Pressure Relieve Device 1"	200	50	100	50	100	3
27	ML27	Fuse Drip Guard	15	5	5	5	7.5	3
28	ML28	Novaris Surge Arrester	30	10	10	10	15	3
29	ML29	Hv Bushing 10nf630	110	30	30	30	50	3
30	ML30	Novaris Scb 1ph 3a 230vac	15	5	5	5	7.5	3

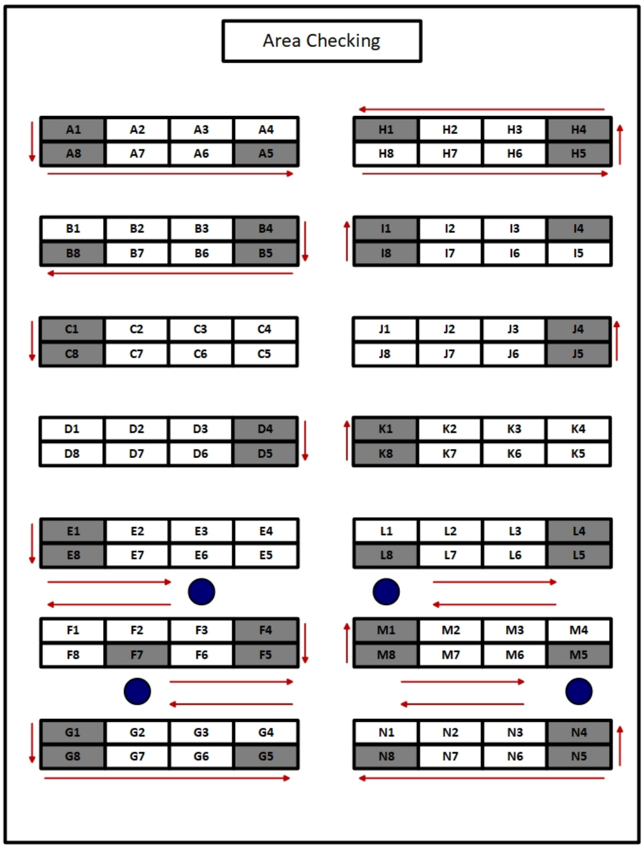

Figure 2. S-Shape flow

4.1. S-shape model

This heuristic creates an order-picking route that visits each aisle containing an item exactly once (see Fig. 2). To apply the concept of dynamic programming, one must define potential states, possible transitions between states, and the associated transition costs. There are six possible transitions, including:

a. Move from the current hallway to the next hallway along the front of the block, traverse the entire hallway, and end at the back of the block.
b. Move from the current hallway to the next hallway along the back of the block, traverse the entire hallway, and end at the front of the block.
c. Move from the current hallway to the next hallway along the front of the block without entering the hallway.
d. Move from the current hallway to the next hallway along the back of the block without entering the hallway.
e. Move from the current aisle to the next aisle along the front of the block, traverse the aisle to the furthest item from the front, and return to the front.
f. Move from the current aisle to the next aisle along the back of the block, traverse the aisle to the furthest item from the back, and return to the back.

There are four key parameters used to calculate the distance traveled by workers in the order-picking process in a warehouse, particularly when using the S-Shape method. The first parameter is S_N, which represents the total distance traveled by workers under current conditions without any route optimization. S_B is the basic distance, referring to the total distance that must be covered in the order-picking process, excluding movement between aisles. $S_A$is the distance across aisles, representing the horizontal distance a worker travels when moving from one aisle to another.

The last parameter is S_W, the distance between aisles, which accounts for the additional distance a worker must cover when passing through an empty aisle or switching aisles without retrieving an item. This distance is calculated based on the aisle width and the number of movements made. S_W is crucial because a higher value increases the time and energy required by workers. The relatoinship among those parameters is expressed in Eq. (1).

$$S_N = S_B + S_W + S_A \qquad (1)$$

4.2. Aisle-by-aisle model

The order-picking route generated by this algorithm passes through each aisle only once. Dynamic programming is used to determine the optimal route for moving from one picking aisle to another while minimizing travel distance. The route begins at the depot and proceeds to the nearest aisle, where the picker collects all items on the picking list. The picker then exits through either the front-cross aisle or the middle-cross aisle to reach the next picking aisle, with decisions based on the shortest distance. This process continues until all picking locations have been visited, after which the picker returns to the starting point. The total distance is also calculated using the Eq. (1).

4.3. Results comparison

This section compares the performance measures of the S-shape method, the aisle-by-aisle method, and the current method used by the warehouse. Table 5 presents the comparison of the S-shape and aisle-by-aisle methods.

Data was collected through a series of 10 trials and analyzed using interactive software to ensure calculation accuracy. Across the 10 trials, varying results were obtained (see Table 5), likely due to differences in conditions during each trial, such as the layout of goods, obstacles along the route, or human factors in decision-making. On average, the "S-Shape" method appears to be more efficient, with an average distance of 678.73 meters, compared to the "Aisle-by-Aisle" method, which has an average distance of 684.04 meters. Based on data processing using InterActive Freight & Warehouse software, a comparison was made between the distance traveled under existing conditions and the distances generated by the S-Shape and Aisle-by-Aisle heuristic methods. The analysis results are shown in Table 6.

The comparison results show that the S-Shape method significantly reduces travel distance compared to the aisle-by-aisle method. The average distance traveled using the S-Shape method is 678.73 meters, while the aisle-by-aisle method reaches 684.04 meters. This reduction in travel distance directly improves operational efficiency, as shorter distances lead to reduced working hours and increased productivity.

The next step is to conduct a mean difference test using a T-test to determine whether there is a significant difference in the results produced by the three methods. This analysis will help evaluate which method provides the most optimal performance in reducing travel distance.

Table 5.
Comparison between S-shape and aisle-by-aisle

Trial	Distance (meters)	
	S-Shape	Aisle by Aisle
1	684.13	689.04
2	683.62	691.17
3	662.43	706.74
4	668.39	668.39
5	681.13	683.44
6	690.43	672.99
7	680.14	671.98
8	669.12	688.99
9	686.77	682.95
10	681.13	684.71
Average	678.73	684.04

Table 6.
Distance calculated

No	Method	Distance (meters)
1	Existing conditions	915
2	S-shape	678.73
3	Aisle-by-aisle	684.04

Table 7.
T-test result

Indicator	Methods	t	sig
Distance (meters)	Existing	2.02	0.029
	S-Shape	2.67	0.023
	Aisle-by-aisle	1.48	0.004

Table 8.
Distance calculated

No	Method	Productivity	Line order
1	Existing conditions	84	2,022
2	Aisle-by-aisle	83	2,006

The results of the T-test calculations (see Table 7) comparing the existing conditions and optimization results show that sig < 0.05 and t > 1.669, meaning that H_0 is rejected and H_a is accepted. This indicates a significant difference between the existing conditions and the optimization results. To further strengthen the statistical analysis, we calculated the 95% confidence interval (CI) for each method, which provides a range in which the true mean difference is expected to fall with 95% certainty. The confidence interval for the S-Shape method is (673.21, 684.25), while for the aisle-by-aisle method, it is (679.56, 688.52). Since there is no overlap between the confidence intervals of the existing condition and the heuristic methods, we conclude that the reduction in travel distance is statistically significant.

Additionally, we computed Cohen's effect size to measure the magnitude of the improvement. The effect size for the S-Shape method compared to the existing condition is d = 2.34, while for the aisle-by-aisle method compared to the existing condition, it is d = 2.21, both of which indicate a large effect. These results confirm that the heuristic methods provide a substantial reduction in travel distance with strong practical significance.

The previous research on heuristic methods based on the Traveling Salesman Problem (TSP) algorithm for optimizing order picking routes demonstrated an average efficiency improvement of 22% in reducing workers' travel distance [7]. Meanwhile, research by [2] found that heuristic strategies such as Return and Midpoint can reduce travel distances by up to 18% compared to conventional methods. The results of this study indicate that the approach used provides comparable outcomes, with a mileage reduction efficiency exceeding 25% compared to existing conditions. Additionally, a study conducted by [20] in a warehouse with a two-cross-aisle layout showed that implementing a heuristic method could reduce travel distances by up to 20% by utilizing an algorithm based on a combination of S-Shape and Largest Gap. These findings confirm that the heuristic method used in this study is highly effective across various warehouse types and layout configurations. To further strengthen the analysis, Cohen's d was calculated to measure the practical significance of the study's results. The S-Shape method demonstrated a large effect (d = 2.34), indicating that the difference between this method and the existing conditions has a substantial impact on improving order-picking efficiency.

4.4. Productivity analysis

Table 8 supports the effectiveness of the proposed method. Productivity in order picking is measured by the number of order lines processed per working hour. An order line represents a unique item line in a single order that must be processed within the warehouse system. The research results indicate that the S-Shape method increases the number of order lines processed from 30 to 84 per hour, while the aisle-by-aisle method reaches 83 per hour.

Productivity in the order picking process is calculated by dividing the total number of order lines successfully picked by the total labor hours used. This ratio reflects the efficiency of the order picking system, with higher values indicating improved performance and reduced operational time.

Based on Table 8, the use of the S-Shape method increases order-picking productivity from 30 to 84 order lines per picker per hour, while the aisle-by-aisle method increases productivity from 30 to 83 order lines per picker per hour. These results highlight the effectiveness of implementing heuristic routing strategies in warehouse operations.

According to [1], increasing the number of order lines processed per hour contributes to higher operational efficiency by reducing search and travel time for workers in the warehouse. A study by [5] also confirms that a more efficient order-picking system can increase throughput and reduce errors in order fulfillment, ultimately leading to higher customer satisfaction. Additionally, research by [16] revealed that applying heuristic algorithms in the order-picking process can increase productivity by up to 30% compared to conventional methods.

Thus, the findings of this study further reinforce that optimization using heuristic methods not only improves travel distance efficiency but also positively impacts order processing capacity and overall warehouse efficiency. In terms of productivity, the S-Shape method yields a slightly higher improvement than the aisle-by-aisle method. This study demonstrates that the S-Shape method allows an increase in the number of order lines processed per hour from 30 to 84, while the aisle-by-aisle method results in an increase to 83 order lines per hour. These findings suggest that although both methods effectively reduce worker travel distances and increase throughput, the S-Shape method provides a slight advantage in productivity due to its more optimal path structure [28].

Furthermore, [29] demonstrated that applying heuristic methods in a scheduling system with limited resources can optimize the distribution of warehouse workers' workload, which is crucial for reducing worker fatigue by minimizing travel distances. Research by [30] also highlights that heuristic methods have been successfully applied in various automated and manual storage systems to improve warehouse efficiency, particularly in optimizing the movement of Automated Guided Vehicles (AGVs) in very narrow aisles.

4.5. Managerial implications

This study's results offer managerial implications for enhancing warehouse efficiency. The S-Shape heuristic method cuts worker travel distance in order picking by over 25% compared to conventional methods, reducing labor costs, energy use, and fatigue for more cost-effective operations. It also boosts order lines processed per hour to 84 (from 30), speeding up the process, improving throughput, and enhancing customer satisfaction. Interactive software for heuristic simulation enables managers to optimize picking routes dynamically based on layout and demand changes, ensuring efficiency under varying conditions. This adaptability improves resource allocation and responsiveness, while integrating heuristics and software supports data-driven decisions for better workflows and productivity.

5. Conclusions

The S-Shape and aisle-by-aisle heuristic routing methods are used to improve and propose new order-picking routes to shorten travel distances. This study successfully identifies the S-Shape method as the most effective, as it results in a shorter travel distance compared to both the current condition and the aisle-by-aisle method. However, this study has several limitations. It was conducted in a warehouse with a specific layout and system, meaning the results may not be fully generalizable to warehouses with different structures, such as automated warehouses or those with dynamic storage systems. While reducing travel distance may help mitigate worker fatigue, this research does not directly measure its impact on productivity. Additionally, real-time fluctuations in volume and demand patterns were not considered in this model.

To expand this research, several future directions can be explored, such as developing AI- and Machine Learning-based models and conducting fatigue analysis to design more ergonomic work strategies.

Declaration statement

Cipto Purwanto: Conceptualization, Methodology, Supervision, Project administration, Software, Validation, Formal Analysis, Writing. Rienna Oktarina: Software, Review & Editing.

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The authors report there are no competing interests to declare.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, [RO], upon reasonable request.

AI Usage Statement

Generative AI and AI-assisted tools were used to enhance the language and readability of this manuscript. The authors have reviewed and revised all AI-generated content to ensure its accuracy and alignment with the research. The authors remain fully responsible for the work's scientific content, conclusions, and integrity, and disclose the use of AI to ensure transparency and adherence to publisher guidelines.

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