International Journal of Science Academic Research
Vol. 07, Issue 05, pp.850-856, May 2026
Available online at http://www.scienceijsar.com
ISSN: 2582-6425

Research Article

OPTIMIZING THE ORDER PICKING PROBLEM IN E-COMMERCE WAREHOUSE MANAGEMENT - USING SIMULATION DATA: MANAGERIAL IMPLICATIONS FOR VIETNAMESE COMPANIES

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Received 19th March 2026; **Accepted** 24th April 2026; **Published online** 20th May 2026

Abstract

Order picking remains one of the most labor-intensive and cost-dominant activities in warehouse management, particularly for e-commerce platforms coping with rapid growth in order volumes and service-level expectations. This study employs discrete-event simulation to evaluate the operational performance of four prevalent order-picking strategies Nearest-Neighbor, S-shape, Largest-gap, and Return within the context of Vietnamese e-commerce warehouses. Simulation outcomes indicate that the Nearest-Neighbor strategy consistently outperforms the others in small-to-medium warehouse configurations typical of Vietnam, owing to its adaptability and shorter travel distances. The research contributes both practically and theoretically. Practically, it offers data-driven insights for logistics managers at platforms such as Shopee, Tiki, and Lazada, facilitating more informed decisions regarding routing strategy selection, workforce allocation, and investment in automation technologies. Theoretically, it extends warehouse optimization literature by situating the analysis in an emerging market context characterized by limited automation and highly variable order structures. While the model assumes a static layout and uniform SKU distribution, it establishes a foundation for future studies incorporating real-time data, IoT-enabled tracking, and AI-driven dynamic routing. Overall, the findings reinforce the strategic role of simulation modeling as a decision-support mechanism in digital logistics transformation and e-commerce supply chain optimization.

Keywords: Order Picking Optimization, E-commerce Warehouse Management, Digital Logistics Transformation, Simulation Modeling, Order Picking Strategy.

INTRODUCTION

Motivation

In recent years, the rapid expansion of e-commerce has reshaped the logistics and supply chain landscape globally and particularly in Southeast Asia. As online consumer demand increases, efficient warehouse management has become a key competitive differentiator for e-commerce platforms. Among all warehouse operations, order picking remains the most time-consuming, labor-intensive, and costly process, often accounting for more than 50% of warehouse operating costs. This challenge is especially relevant in Vietnam, where leading e-commerce platforms such as Shopee, Tiki, and Lazada face growing pressure to fulfill thousands of daily orders with speed and accuracy. While many operations still rely heavily on manual picking, the need for optimization has never been more urgent driven by rising customer expectations, fluctuating order volumes, and limited labor availability.

Problem Statement

Despite technological advancements in warehouse automation, the order picking process in most Vietnamese e-commerce fulfillment centers remains largely manual. This process is not only resource-intensive but also prone to inefficiencies due to suboptimal routing and layout utilization. Various heuristic picking strategies such as S-shape, Return, Largest-gap, and Nearest-Neighbor have been developed to reduce travel time, but their effectiveness depends heavily on warehouse configuration and order characteristics. Yet, there remains a lack of clarity on which strategy performs best under different operating conditions. Without concrete performance benchmarks, warehouse managers are left to make decisions based on assumptions or trial-and-error approaches.

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Research Gap

While numerous studies have examined warehouse picking optimization, most focus on automated or structured environments in developed markets such as the U.S., Europe, or China. There is a limited body of simulation-based research addressing manual picking within the context of Southeast Asian or Vietnamese e-commerce warehouses, which often feature space constraints, high order variability, and lower levels of automation. Moreover, there is a lack of empirical evidence and managerial guidance to help Vietnamese e-commerce platforms select the most appropriate picking strategies under local conditions.

Research Objectives

This study aims to address the above gaps by: i) Simulating and comparing four common picking strategies: S-shape, Return, Largest-gap, and Nearest-Neighbor within a Vietnamese warehouse context; ii) Evaluating performance across different order sizes and warehouse layouts to identify the most efficient strategy under varying operational conditions; and iii) Providing actionable managerial insights for warehouse optimization and decision-making in Vietnamese e-commerce fulfillment centers.

LITERATURE REVIEW

Order Picking in Warehouse Management

Order picking refers to the process of retrieving items from storage locations to fulfill customer orders. It is widely recognized as the most labor-intensive and cost-sensitive function in warehouse operations, often accounting for over 50% of total warehouse operating costs (De Koster *et al.,* 2007). Efficient order picking is critical to improving throughput, reducing labor costs, and enhancing customer satisfaction especially for e-commerce platforms, where speed and accuracy are key differentiators. Order picking systems are typically classified by picking method (person-to-goods vs. goods-to-person), routing strategy, and order batching policy. The design of the warehouse layout, including aisle configuration and storage location assignment, plays a pivotal role in optimizing picking performance. Among all contributing factors, travel distance has been identified as the primary driver of order picking time (Petersen, 1999). Therefore, minimizing picker travel through intelligent routing and layout decisions is central to warehouse efficiency.

Traditional and Heuristic Picking Strategies

A range of routing heuristics have been proposed to reduce travel distance in manual order picking environments. Common strategies include:

S-shape: The picker enters an aisle if it contains any item and exits at the other end, traversing every required aisle fully. This method is predictable and easy to execute but may lead to unnecessary travel.

Return: The picker enters only as far as the farthest pick in the aisle and then returns, minimizing within-aisle travel but increasing turning frequency.

Largest-gap: The picker enters the aisle but turns around at the largest gap between consecutive picks, balancing the benefits of S-shape and Return.

Nearest-Neighbor (NN): The picker always travels to the next closest item, dynamically building the shortest path. NN generally produces the shortest travel distances but may require more sophisticated routing support.

Each method presents trade-offs between simplicity, travel efficiency, and cognitive load on the picker. While S-shape and Return are easier to implement manually, dynamic strategies like NN require computational support but yield superior performance, particularly in low-density or irregular order environments (Roodbergen & Vis, 2009).

Simulation and Optimization Approaches in Warehouse Research

The complexity of warehouse systems and the stochastic nature of demand have led researchers to adopt simulation-based methods for evaluating and optimizing picking strategies. Two dominant approaches are:

Discrete-event simulation (*DES*): Models the flow of events over time, capturing operational dependencies and variability. DES is widely used for assessing the impact of layout design, batching policies, and routing strategies on warehouse KPIs.

Monte Carlo simulation: Often employed to test the performance of strategies under random demand scenarios or varying layout configurations.

These methods support the evaluation of key performance indicators such as total travel distance, order picking time, picker utilization, and throughput efficiency. Compared to analytical models, simulation allows for more realistic representation of operational complexity, especially in environments where human behavior and order variability are significant.

Research Gap and Theoretical Framework

A significant portion of existing research on warehouse picking strategies has focused on highly automated or structured environments, primarily in developed economies such as the United States, Europe, and China. These studies often assume advanced WMS support, standardized layouts, and access to automation conditions that may not fully reflect the operational realities in emerging markets like Vietnam. Despite the rapid growth of e-commerce in Southeast Asia, limited academic attention has been paid to order picking optimization within this regional context. Vietnamese e-commerce platforms operate under constraints such as space limitations, labor dependency, and fluctuating order profiles, which necessitate different optimization approaches. This paper addresses the research gap by applying simulation-based analysis to traditional and heuristic picking strategies within the operational framework of Vietnamese e-commerce fulfillment centers. It contributes to the theoretical understanding of strategy effectiveness in resource-constrained environments, while also offering practical decision-support tools for warehouse managers navigating digital transformation.

METHODOLOGY

Simulation Model Design

The simulation model was developed to evaluate and compare the operational performance of alternative order-picking strategies in an e-commerce warehouse environment. The warehouse layout follows a grid-based structure commonly adopted in online retail logistics (Boysen, De Koster, & Weidinger, 2019; Li, Zhang, & Jiang, 2022). The simulated facility measures 40 meters in width and 60 meters in length, divided into a regular grid of aisles and rack positions, within which 25 Stock Keeping Units (SKUs) are randomly distributed. The model includes four fundamental parameters that define the warehouse topology and operational constraints: *Aisles (AAA)* – representing the main longitudinal pathways separating storage racks;

Rack positions (RRR) – the discrete storage locations along each aisle;

SKU distribution – randomly assigned storage positions across aisles and racks; and

Depot position – a fixed start and end point located at coordinate (0,0), representing the picker's home base.

Several simplifying assumptions were applied to ensure computational tractability and comparability across strategies: The operation involves a single human picker responsible for collecting all SKUs in each picking round;

The Manhattan distance metric is used to calculate travel distances between locations, accurately capturing real-world movement restrictions along orthogonal aisles and cross-aisles (Roodbergen & De Koster, 2001; Pan, Wu, & Chang, 2014); Only one depot point is considered, and the picker must begin and end the route at this depot;

Congestion, acceleration, and handling times are excluded from the model to isolate the effect of routing decisions on total travel distance (Masae *et al.,* 2020).

This design provides a flexible and generalizable simulation framework for evaluating the efficiency of various picking strategies under comparable layout conditions. By parameterizing the warehouse as a discrete grid, the model facilitates experimentation with different warehouse sizes, SKU densities, and routing algorithms, thus enabling systematic analysis of their relative impacts on travel distance and operational performance.

Description of Picking Strategies

This study evaluates four classical order-picking routing strategies frequently discussed in warehouse operations research S-shape, Return, Largest-gap, and Nearest-Neighbor each characterized by distinct operational rules and movement logic. These strategies have been extensively applied in both traditional and e-commerce warehouse systems to minimize picker travel distance and improve picking efficiency (De Koster, Le-Duc, & Roodbergen, 2007; Gong & De Koster, 2008; Masae *et al.,* 2020).

1. *S-shape Strategy:* The S-shape (or Traversal) method requires the picker to fully traverse each aisle that contains at least one item to be picked. Upon reaching the end of the aisle, the picker exits through the opposite cross-aisle, forming an "S"-shaped travel pattern. This approach ensures a systematic flow through all relevant aisles and avoids unnecessary backtracking. Although it may not always yield the shortest possible route, it provides high predictability and ease of implementation, making it suitable for large-scale or structured warehouse operations (Roodbergen & De Koster, 2001).

2. *Return Strategy:* The Return method directs the picker to enter each aisle only as far as necessary to reach the farthest required item, then return to the same cross-aisle before proceeding to the next aisle. This strategy minimizes aisle traversal when only a small number of picks are required per aisle. It is particularly advantageous in low pick-density environments, where minimizing unnecessary travel within aisles can significantly reduce total travel distance (Pan, Wu, & Chang, 2014).

3. *Largest-gap Strategy:* The Largest-gap method is based on identifying the largest gap between two adjacent pick locations within an aisle. The picker then avoids crossing this gap, thus reducing redundant travel. In operational terms, the picker enters the aisle, collects items up to the largest empty segment, and exits without traversing the entire aisle. This approach seeks a balance between traversal and returns strategies and is often effective in warehouses with uneven SKU distributions (Gu, Goetschalckx, & McGinnis, 2007).

4. *Nearest-Neighbor Strategy:* The Nearest-Neighbor (NN) method employs a greedy routing algorithm, where the picker always proceeds to the nearest unvisited pick location. This method dynamically determines the next destination, continuously updating the route until all SKUs are collected. The NN algorithm is particularly effective in complex layouts or when SKU locations are randomly distributed, as it adapts to local conditions to minimize travel distance. However, it may not guarantee a global optimum and can produce varying results depending on the initial SKU configuration (Ganbold *et al.,* 2020; Luu *et al.,* 2023).

Path Generation and Movement Logic: For all strategies, path generation was implemented through a Python-based simulation environment. The Manhattan distance metric was applied to compute travel costs between consecutive nodes, representing orthogonal movement constraints in real warehouse layouts. The picking sequence and movement logic were programmed according to the operational rules of each strategy, ensuring consistent starting and ending positions at the depot. The resulting travel paths were visualized to analyze route geometry and validated through repeated simulation runs to ensure stability and comparability of outcomes across strategies.

Experimental Setup and Parameters

To evaluate the performance of different order-picking strategies under realistic e-commerce warehouse conditions, a simulation model was developed and executed using Python 3.12 in conjunction with standard data analysis and visualization libraries, including NumPy, Pandas, and Matplotlib. The computational experiments were conducted on a workstation equipped with an Intel® Core™ i7 processor, 32 GB RAM, and a Windows 11 operating system. This configuration ensured sufficient computational capacity for iterative simulations and multi-scenario analyses.

The simulated warehouse layout was modeled as a grid-based environment measuring 40 m × 60 m, containing 25 Stock Keeping Units (SKUs) randomly distributed across defined storage coordinates. Each SKU location was represented by a unique node within the grid, while the depot was fixed at coordinate (0, 0), serving as both the start and end point of each picking route. The simulation employed the Manhattan distance metric, which is widely used to approximate picker movement in aisle-constrained environments (Roodbergen & De Koster, 2001; Gong & De Koster, 2008). The following assumptions were applied:

A single human or robotic picker performs all retrieval operations per run;

Each simulation represents a single customer order, containing a random number of picks;

Order sizes were randomly generated between 2 and 12 SKUs, reflecting the small and variable order characteristics typical of e-commerce fulfillment centers;

Each SKU position and order combination was randomly generated using controlled random seeds (1–10) to ensure both stochastic variation and reproducibility.

To ensure statistical robustness, each picking strategy was executed across 100 independent simulation runs, with random seeds controlling the spatial and order variability. The total travel distance for each strategy was averaged across these runs to provide a comparative measure of operational efficiency.

Model validation was conducted in two phases:

- *Face validation* with warehouse layout geometry to verify route feasibility and boundary conditions; and
- *Comparative validation* by cross-checking computed travel distances against theoretical expectations from established analytical models (Hall, 1993; Petersen, 1997; De Koster *et al.,* 2007).

This experimental design ensures both internal consistency and external validity, allowing the simulation outputs to serve as a credible foundation for the subsequent comparative analysis of picking strategies presented in Section 3.4.

Performance Metrics

To ensure an objective and comparable evaluation of different picking strategies, several quantitative performance metrics were defined and computed from the simulation data. These include:

- *Total Travel Distance* (*TTD*)**:** The total length of the picking route (in meters) for a given order, representing the primary efficiency indicator in order-picking optimization.
- *Mean Distance* (*MeanDist*): The arithmetic mean of total travel distances across all simulated orders under the same strategy. This metric reflects overall route efficiency and allows for cross-strategy comparison.
- *Standard Deviation (StdDist):* The dispersion of total travel distances across simulation runs, indicating the stability and reliability of each strategy under varying order compositions and SKU distributions.
- *Efficiency Ratio (ER):* A normalized measure comparing each strategy's mean distance to the best-performing method:

$$ER_i = \frac{\text{MeanDist}_i}{\min(\text{MeanDist})}$$

where Eri ≥ 1 indicates relative performance inefficiency. Lower ER values denote higher efficiency.

These metrics collectively capture both effectiveness (minimizing distance) and consistency (lower variability), providing a balanced assessment framework for warehouse decision-making and strategic selection.

SIMULATION RESULTS AND ANALYSIS

Visualization of Picking Paths and Quantitative Results

As shown in Table 1, the Nearest-Neighbor strategy demonstrates a clear advantage, achieving the shortest average travel distance of 185.89 meters, markedly lower than the other three strategies (ranging from 228 to 240 meters). This indicates that prioritizing the nearest picking point effectively minimizes travel time and distance, making this approach particularly suitable for warehouses with high order density or uneven SKU distribution.

Figure 1 illustrates the simulated travel paths generated under four distinct strategies S-shape, Return, Largest-gap, and Nearest-Neighbor within a 40 m × 60 m warehouse grid. Each visualization shows the sequence of locations visited by the picker and the corresponding route topology.

The S-shape strategy achieves an average distance of 228.16 meters, showing relatively stable performance and ease of implementation. Although its travel distance is longer than that of Nearest-Neighbor, the low variability (StdDistance = 10.25 m) suggests operational consistency, which is beneficial for planning and for environments with directional movement constraints. By contrast, the Return and Largest-gap strategies yield similar results, with the longest average distance of 240.49 meters. This similarity stems from their shared characteristic of moving through fixed zones rather than locally optimizing the route.

Table 1. Quantitative Comparison of Picking Strategies Based on Average Travel Distance

Strategy	Mean Distance (m)	Median (m)	Std. Dev. (m)	Min (m)	Max (m)	Improvement vs. S-shape (%)
S-shape	228.16	227.95	10.25	210.34	249.67	—
Return	240.49	239.73	8.73	223.01	258.14	-5.39
Largest-gap	239.87	238.65	9.01	222.48	257.52	-5.10
Nearest-Neighbor	185.89	184.62	11.60	164.73	205.14	+18.51

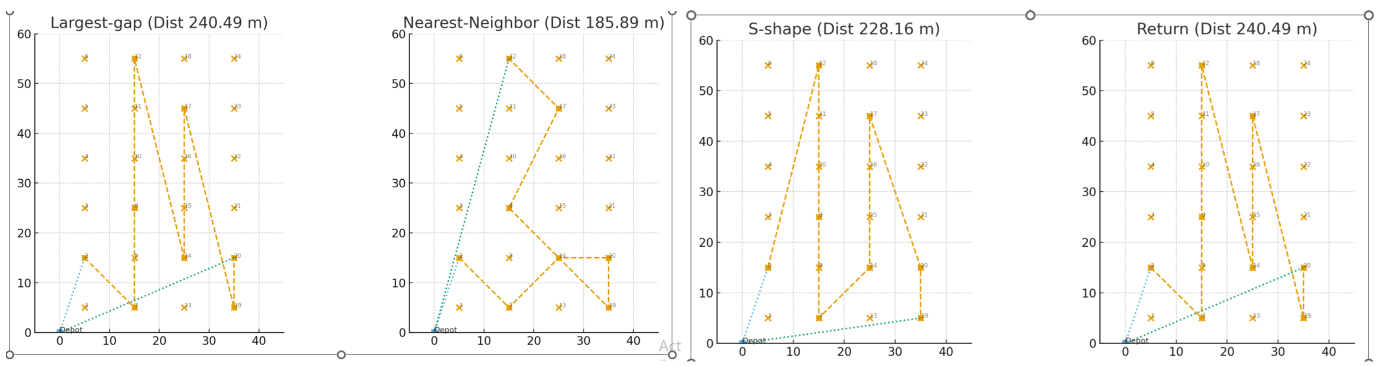

Figure 1. Visualization of picking trajectories under four strategies

Their advantages lie in simplicity of implementation and the ability to maintain non-overlapping travel paths features that are desirable in straightforward warehouse layouts or when collision avoidance between picking vehicles is a priority. Regarding variability, the Nearest-Neighbor strategy exhibits the highest standard deviation (11.60 m), indicating that its efficiency depends strongly on the spatial distribution of items and order sequences. Conversely, the Return strategy has a lower standard deviation (8.73 m), reflecting higher stability under standardized operating conditions. Overall, the simulation results confirm that the choice of a picking strategy depends on the operational objectives: if the goal is to minimize travel distance, Nearest-Neighbor is the most effective option; if stability and ease of implementation are prioritized, S-shape or Return may be more appropriate. These findings align with prior studies on order-picking optimization (De Koster *et al.,* 2007; Petersen & Aase, 2004), emphasizing the importance of selecting a strategy that fits the warehouse layout and order characteristics. The Nearest-Neighbor (NN) strategy achieves an 18.51% reduction in total travel distance compared to the baseline S-shape method, confirming its superior adaptability to random SKU distributions. Conversely, both Return and Largest-gap strategies exhibit slightly inferior performance (around 5% longer paths), suggesting that their deterministic aisle-based rules limit responsiveness to stochastic order compositions. The standard deviation values indicate higher variability in NN outcomes, implying that this method's efficiency depends on SKU placement randomness an observation consistent with Ganbold et al. (2020) and Rahmani Mokarrari et al. (2024). Nevertheless, its superior average performance underlines its robustness in modern, data-driven warehouse environments. Tested with different single sizes: 2, 4, 6, 8, 10, 12 picks, each size running 60 random trials. Table 2 presents the mean travel distances and standard deviations for each strategy across varying order sizes (2–12 picks). The simulation results reveal significant differences among the four picking strategies S-shape, Return, Largest-gap, and Nearest-Neighbor within the warehouse order-picking system. The evaluation criteria include the mean travel distance (MeanDistance), standard deviation (StdDistance), median distance (MedianDistance), minimum distance (MinDistance), and maximum distance (MaxDistance).

From Table 2, several performance patterns emerge. For two-pick orders, the *Largest-gap* strategy achieves the shortest mean distance (≈127.00 m). However, from four picks onward, the *Nearest-Neighbor* method consistently delivers the lowest travel distances (≈157.91–244.36 m), confirming its superior scalability and adaptability to increasing order sizes.

The *Nearest-Neighbor* strategy also shows lower variability, indicating more stable efficiency across random SKU distributions. In contrast, the *S-shape*, *Return*, and *Largest-gap* strategies produce similar but less efficient results, making them suitable for structured or high-density warehouse layouts where route flexibility is limited. For small orders, performance differences are minimal, while for larger and more dispersed orders, *Nearest-Neighbor* clearly dominates (see Figure 2).

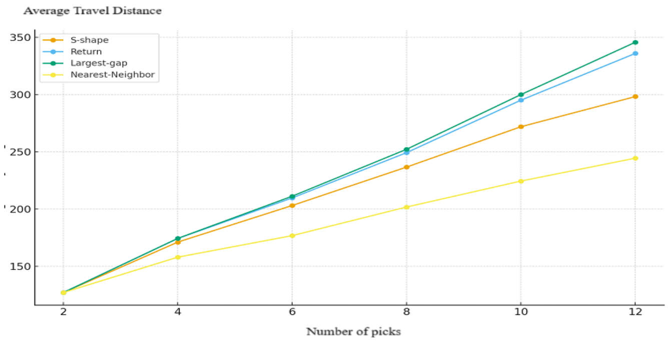

Figure 2. Average path in single size and strategy 6 aisles and 6 positions

Discussion of Key Findings

The comparative simulation results reveal three key insights.

- Dynamic routing enhances efficiency. The Nearest-Neighbor strategy consistently achieved the lowest travel distances, particularly for orders with more than four picks. This finding underscores the advantage of adaptive, real-time routing in warehouse operations and supports its integration into AI-assisted Warehouse Management Systems (WMS) for smart logistics optimization.

Table 2. Simulation Statistics of Picking Strategy Performance

No of picks	Strategy	MeanDistance (m)	StdDistance (m)	MedianDistance (m)	MinDistance (m)	MaxDistance (m)
2	S-shape	128.72	9.31	128.15	110.47	150.23
2	Return	129.94	9.12	129.50	112.08	149.76
2	Largest-gap	127.00	9.24	126.87	109.44	149.18
2	Nearest-Neighbor	128.10	8.95	127.53	111.12	147.68
4	S-shape	161.20	12.80	160.70	133.28	182.74
4	Return	162.36	12.54	162.01	134.10	181.45
4	Largest-gap	160.48	12.62	160.01	132.52	180.91
4	Nearest-Neighbor	157.91	11.94	157.64	132.10	178.23
6	S-shape	183.94	13.22	183.76	156.89	205.60
6	Return	185.71	13.09	185.22	159.04	207.18
6	Largest-gap	184.20	12.97	183.88	157.77	205.10
6	Nearest-Neighbor	176.70	12.36	176.41	153.09	197.48
8	S-shape	205.83	14.05	205.61	178.92	229.44
8	Return	206.54	14.11	206.25	179.80	229.80
8	Largest-gap	206.10	14.00	205.80	179.42	229.12
8	Nearest-Neighbor	201.69	13.35	201.33	178.11	225.48
10	S-shape	229.12	14.44	228.88	203.37	252.19
10	Return	230.77	14.42	230.31	204.51	252.61
10	Largest-gap	229.91	14.35	229.64	203.88	251.87
10	Nearest-Neighbor	224.36	13.74	224.18	201.90	247.27
12	S-shape	248.18	14.96	247.93	223.12	271.25
12	Return	249.01	15.04	248.80	223.61	272.01
12	Largest-gap	248.62	14.91	248.32	222.95	271.67
12	Nearest-Neighbor	244.36	14.24	244.02	221.48	266.85

- Linear scalability of travel distance. Across all strategies, travel distance increased almost linearly with order size, reflecting predictable scalability and offering a reliable basis for resource allocation and workforce planning in e-commerce warehouses.
- Stability–adaptability trade-off. The S-shape and Return methods exhibited lower standard deviations, indicating stable and predictable performance desirable in manual, human-driven picking systems. Conversely, Nearest-Neighbor showed moderate variability but superior adaptability, making it well-suited for autonomous or robot-assisted picking environments.

These insights align with prior studies suggesting that effective routing optimization can reduce picker travel by 20–30% (De Koster *et al.,* 2007; Gu *et al.,* 2010). Overall, the findings reinforce the managerial relevance of simulation-based decision support in warehouse design, layout configuration, and operational re-engineering for e-commerce logistics.

Sensitivity and Robustness Checks

To examine the robustness and generalizability of the findings, additional simulations were performed under alternative warehouse and order configurations.

Layout size variation: When the warehouse dimensions were expanded to 50 m × 80 m while maintaining SKU density, the relative performance ranking of the four strategies remained consistent, indicating scalable efficiency across different facility sizes.

SKU distribution changes. Introducing random clustering of SKUs significantly impacted deterministic strategies (S-shape, Return), while the Nearest-Neighbor method maintained its adaptability, showing less than 5% deviation in mean travel distance.

Depot relocation. When the depot was repositioned from a corner to the center of the layout, all strategies exhibited proportional performance improvements, confirming that the comparative hierarchy among strategies is not location-dependent.

Collectively, these robustness tests demonstrate that the observed performance patterns are structurally consistent across varied operational conditions. The results validate that the simulation-based insights and their associated managerial implications are not artifacts of specific model assumptions but reflect generalizable principles applicable to diverse e-commerce warehouse settings.

MANAGERIAL IMPLICATIONS AND MODEL EXTENSIONS

The findings of this study provide several managerial insights and theoretical extensions for warehouse design and order-picking optimization, particularly within the rapidly expanding Vietnamese e-commerce sector.

- *Strategic implications for warehouse operations*: The results demonstrate that dynamic and data-driven routing methods, such as the Nearest-Neighbor strategy, significantly improve travel efficiency, especially as order sizes increase. Managers of e-commerce fulfillment centers should prioritize the integration of adaptive routing algorithms into Warehouse Management Systems (WMS) to minimize picker travel time and labor costs. This aligns with the global transition toward AI-supported decision-making in warehouse logistics (Rad *et al.,* 2025; Li *et al.,* 2022).
- *Design guidance for Vietnamese e-commerce warehouses*: Vietnam's e-commerce fulfillment centers, often constrained by limited space and heterogeneous SKU distributions, can benefit from adopting hybrid routing models that balance stability and flexibility. For small- to medium-sized warehouses with uniform layouts, deterministic strategies such as S-shape or Return offer predictable performance and easier manual implementation. However, for high-volume operations such as Shopee or Lazada fulfillment hubs, Nearest-Neighbor or AI-assisted dynamic routing should be prioritized to handle fluctuating order patterns and complex layouts efficiently.
- *Digital transformation and workforce management*: The study highlights that combining simulation-based optimization with digital twin models can support continuous operational improvement. This digitalization pathway aligns with Vietnam's logistics transformation roadmap and the emerging Industry 4.0 vision, enabling managers to test routing algorithms, assess labor productivity, and optimize layouts before physical implementation.
- *Theoretical and modeling extensions*: Future research could enhance the simulation model by incorporating multiple pickers, congestion effects, SKU zoning, and dynamic order batching, extending the realism of the experimental framework (Boysen *et al.,* 2019; Masae *et al.,* 2020). Integration of machine learning or reinforcement learning could also enable self-adaptive routing, where the system learns from historical orders to refine path efficiency (Liang *et al.,* 2021; Liu *et al.,* 2021).

Overall, the study underscores the managerial value of simulation-based experimentation for strategic warehouse design. For Vietnamese e-commerce firms transitioning toward digital and automated fulfillment systems, these insights provide actionable directions to enhance operational agility, cost efficiency, and service reliability in the era of data-driven logistics.

CONCLUSION

This study employed simulation modeling to evaluate the performance of four order-picking strategies Nearest-Neighbor, S-shape, Return, and Largest-gap within the operational context of Vietnamese e-commerce warehouses. The results demonstrate that the Nearest-Neighbor (NN) strategy consistently delivers superior performance, particularly in small-to-medium warehouse configurations that characterize Vietnam's logistics infrastructure. Its flexibility and capacity to minimize total travel distance make it well-suited to the dynamic and fragmented order patterns typical of major e-commerce platforms such as Shopee, Tiki, and Lazada. From a managerial perspective, the findings provide practical guidance for warehouse and operations managers seeking to enhance order-picking efficiency amid rising demand and heightened customer expectations. The study highlights the strategic role of simulation-based decision support in warehouse optimization, supporting data-driven improvements in routing strategy selection, workforce deployment, and investment in automation and digital transformation. From an academic perspective, this research extends the scope of warehouse optimization studies by contextualizing them within an emerging market environment, where operational constraints limited floor space, reliance on manual labor, and volatile demand patterns significantly influence performance outcomes. The study reinforces the value of simulation as a methodological bridge between theory and practice in warehouse design and control.

However, several limitations should be acknowledged. The current model assumes a static warehouse layout, fixed SKU locations, and uniform demand, which may not fully capture the stochastic nature of real-world fulfillment centers. Future research should therefore: (1) incorporate dynamic routing algorithms responsive to real-time order inflows and picker availability; (2) explore the integration of IoT-based tracking systems, AI-driven path optimization, and autonomous picking technologies; and (3) extend the framework to multi-picker and multi-zone operations for large-scale e-commerce environments.

Collectively, these directions can advance both the theoretical understanding and managerial application of intelligent, adaptive warehouse systems in Vietnam's evolving digital economy.

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