

Cost Minimization in 3D Bin Packing under Orientation and Operational Constraints: A Case Study in E-Commerce Fulfillment

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Abstract—Inefficient parcel packing in e-commerce fulfillment causes excessive void space, inflated dimensional weight charges, and unnecessary dunnage costs. This issue is rightly classified as a three-dimensional bin packing problem (3D-BPP), which is NP-hard and computationally intractable at realistic scales. Current industry practice relies on manual, horizontal-only packing with predefined box sizes, thereby systematically overlooking opportunities to reduce costs through flexible orientation. While extensive literature addresses 3D-BPP, existing research typically applies operational constraints as post hoc checks after geometric optimization, and rarely combines discrete box selection with explicit logistics cost minimization. This study develops and evaluates an orientation-flexible packing framework that integrates fragility protection, weight precedence, and base-support stability into the heuristic placement process, rather than filtering out infeasible solutions after packing. The framework selects from a set of discrete, predefined box sizes and minimizes the total logistics cost, including packaging and dimensional weight charges. Three strategies—a horizontal-only baseline, First Fit Decreasing (FFD), and Best Fit (BF) with orientation flexibility, are systematically compared using simulation experiments on 600 real-world e-commerce orders from a personal care products fulfillment operation. Results demonstrate that BF achieves a 4.47% reduction in total logistics cost, 9.31% reduction in void space, and 9.31% reduction in dunnage cost relative to the baseline. At the same time, FFD is approximately eight times faster than BF, with moderate efficiency gains. Cross-validation confirms solution stability across heterogeneous subsets of orders, and sensitivity analyses verify robustness to variations in support thresholds, dimensional-weight pricing, and box-material costs. These findings provide actionable guidance for context-dependent

strategy selection, demonstrating that integrating operational constraints into packing heuristics do not degrade cost performance and remain computationally feasible for real-world e-commerce fulfillment.

Index Terms—Three-Dimensional Bin Packing, Parcel Packing Optimization, E-Commerce Logistics, Heuristic Algorithms, Transport Efficiency, Supply Chain Cost Management

I. INTRODUCTION

Global e-commerce expansion has fundamentally transformed supply chain dynamics, with operational efficiency at each stage of fulfillment becoming critical to profitability and customer satisfaction [1], [2]. Parcel packing is the process of placing items into shipping containers and is one of the most cost-significant activities in this ecosystem [3]. When packing is done inefficiently, it generates excessive void space, inflating packaging material consumption and disposal costs [4], while dimensional weight pricing penalizes oversized parcels by charging transportation costs proportional to package dimensions rather than actual weight [5]. For high-volume operations, cumulative packing inefficiencies translate into millions of dollars in unnecessary annual logistics expenditure.

Parcel packing is formally recognized as a three-dimensional Bin Packing Problem (3D-BPP), an NP-hard combinatorial optimization problem for which no polynomial-time algorithm guarantees an optimal solution at realistic scales [6]–[8]. Consequently, practitioners rely on heuristic approaches that sacrifice theoretical optimality for computational tractability [9]. Current industry practice involves manual labor guided by simple rules: selecting box sizes from predefined standard cartons and arranging items in fixed horizontal orientation [10]. This method creates systematic inefficiencies, restricting items to horizontal placement forces workers to select oversized containers when tall products consume excessive floor area, even

though smaller boxes would suffice if items could rotate. Moreover, manual packing typically disregards economic factors, basing decisions on geometric feasibility rather than explicitly considering box costs, dimensional weight charges, or dunnage expenses [11].

Despite the substantial body of literature on 3D-BPP that addresses exact algorithms, classical heuristics, and metaheuristics, several important gaps remain [7]. To begin with, most existing studies prioritize geometric packing efficiency, treating operational constraints such as product fragility, load-bearing capacity, and stacking stability as secondary considerations rather than embedding them as core components of the optimization model [10], [12]. Related to this, the discrete nature of box selection in real-world fulfillment operations is frequently overlooked. Many models either assume continuous container dimensions or frame the objective purely as minimizing bin count, neither of which reflects how carton selection actually works in practice [1].

A further gap is the lack of a method for comparing heuristic algorithms in real-world settings. Although First Fit Decreasing (FFD) and Best Fit (BF) are widely recognized as practical packing strategies, their relative performance in settings that simultaneously involve orientation flexibility, operational constraints, and discrete box selection has received limited empirical attention. Lastly, integration of packing decisions with logistics economics remains underexplored, with most models optimizing space utilization without incorporating packaging material costs, dimensional weight charges, or vehicle utilization impacts.

This study addresses these gaps through a simulation-based comparative analysis of orientation-flexible packing strategies under realistic operational constraints. Three objectives guide the investigation. The first is to develop a three-dimensional packing framework that allows full orientation flexibility while embedding operational constraints, including fragility protection, weight precedence, and stacking stability, directly into the optimization logic, alongside discrete box selection and cost-based objective functions. The second objective is to systematically compare the FFD and BF heuristics across three performance dimensions: Cost efficiency, space utilization, and computational tractability. The third is to quantify the economic consequences of permitting orientation flexibility relative to conventional horizontal-only packing, with particular attention to packaging material expenditures, carrier-imposed dimensional-weight charges, and the cost of protective void fill.

The simulation employs operational data from a personal care products e-commerce fulfillment operation. It evaluates three packing strategies:

A horizontal-only baseline representing current practice, and orientation-flexible FFD and BF implementations across 600 customer orders with heterogeneous items. All strategies operate under identical constraints, including discrete box selection (four predefined standard sizes), fragility-based stacking rules, weight precedence requirements, and minimum base-support-area constraints. Performance is measured across economic (total logistics cost, packaging cost, dunnage cost), spatial efficiency (void volume, packing density), and computational (runtime per order) metrics.

II. LITERATURE REVIEW

Three-dimensional bin packing has evolved from pure geometric optimization into a contested space where theoretical elegance confronts operational reality. The problem's NP-hard complexity initially drove research toward computational tractability, and accepting heuristic approximations over exact solutions became the pragmatic consensus [13], [14]. This shift enabled practical implementation at scale, yet introduced a subtler challenge: the optimization objectives themselves diverged from industrial requirements. Academic models optimized what could be easily formulated, volumetric efficiency, bin count minimization, while practitioners needed what remained difficult to encode, cost minimization under safety constraints, discrete box selection, and dimensional weight pricing. This misalignment persists as a defining tension in contemporary research.

Orientation flexibility emerged as a compelling solution pathway, with empirical evidence showing 5-15% volumetric improvements when items could rotate freely rather than remain fixed horizontally [15], [16]. The logic appeared straightforward, i.e., more geometric degrees of freedom enable denser configurations. Yet this geometric promise created an operational paradox. Allowing full rotational freedom maximized space utilization but violated fundamental handling principles, such as placing fragile items sideways, stacking heavy objects atop breakables, and products lacking adequate base support. The literature's response revealed an uncomfortable reality: Operational constraints were treated as post-optimization filters, secondary concerns to be checked after geometric solutions were generated [10]. This sequential approach optimizes geometry first, validates safety second, and proves computationally wasteful when constraint violations necessitate solution rejection and re-optimization, and is philosophically troubling for prioritizing abstract efficiency over tangible product protection.

The algorithm selection debate centers on a deceptively simple trade-off between First Fit Decreasing and Best Fit heuristics. FFD's greedy

strategy places each item in the first feasible location, has linear computational complexity, and is straightforward to implement [17], [18]. BF's exhaustive evaluation of all placement options yields only marginal improvement in superior packing density at substantially higher computational cost [19]. Conventional wisdom, largely derived from unconstrained continuous optimization contexts, favors BF when solution quality justifies an extended runtime. However, this recommendation rests on assumptions that have rarely been tested under realistic conditions. When discrete box catalogs limit container choices, when operational constraints restrict feasible placements, when real-time fulfillment demands rapid decisions, does BF's theoretical advantage persist or collapse under constraint pressure? The literature provides surprisingly limited empirical guidance on this fundamental implementation question [20], [21].

Recent advances in deep reinforcement learning have opened new pathways for online bin packing optimization. Multiple studies demonstrate that DRL-based approaches can outperform traditional heuristics while maintaining computational tractability for real-time applications [22], [23]. However, integrating physical-constraints stability validation, load-bearing requirements, and orientation restrictions within DRL frameworks remains an active research challenge [10]. The integration of heuristic methods with learning-based approaches shows particular promise, with hybrid frameworks achieving competitive results across diverse problem instances [15], [24].

Perhaps the most consequential disconnect involves economic optimization. Academic formulations predominantly minimize bin counts or maximize volumetric utilization metrics, offering intuitive geometric appeal but limited economic relevance [7], [10]. Industrial packing decisions, conversely, occur within explicit financial frameworks in which dimensional weight pricing formulas convert package dimensions into transportation charges, where discrete box catalogs assign differential material costs to size selections, and where void filling requirements create dunnage expenses proportional to unused space [25]–[27]. A configuration achieving 95% space utilization in a large box may incur a higher total cost than a configuration achieving 85% space utilization in a smaller box when dimensional weight penalties dominate material savings. This economic reality requires objective functions directly targeting cost minimization rather than treating volumetric efficiency as a proxy. Yet empirical validation of cost-aware algorithms under realistic pricing structures, actual box catalogs, and genuine operational data remains conspicuously absent from published research [28].

Constraint programming and integer linear programming approaches have demonstrated effectiveness in handling complex multidimensional packing scenarios with safety and stability requirements [29]–[31]. These methods provide provably optimal solutions for small instances but struggle to scale for large-scale real-world problems. Consequently, researchers have increasingly focused on hybrid approaches that combine exact optimization techniques with metaheuristic search strategies [24]–[33].

These tensions converge in a fundamental integration challenge: Can orientation flexibility, operational safety constraints, discrete box selection, and economic optimization coexist within computationally tractable frameworks? Recent attempts to embed constraints directly into optimization logic, rather than apply them post hoc, represent methodological progress, yet joint consideration remains incomplete. Models integrate fragility, orientation, or discrete economics, but rarely all simultaneously. This fragmentation reflects not merely research specialization but deeper uncertainty about whether these objectives fundamentally conflict or can be harmonized. The present study addresses this integration challenge directly by embedding operational constraints into orientation-flexible heuristics operating on discrete box catalogs with explicit cost functions. Rather than assuming constraint-efficiency trade-offs, we empirically assess whether such trade-offs exist under realistic conditions, using operational data to test whether the perceived tension between safety and optimization reflects genuine incompatibility or an implementation artifact. This positioning tests theoretical assumptions against operational reality, distinguishes the contribution from prior work that either sacrificed realism for theoretical tractability or implemented solutions without systematic performance validation.

III. METHODOLOGY

A. Research Design

This study employs computational simulation-based experimental design to evaluate heuristic packing strategies under realistic operational constraints. The methodology addresses three research objectives through controlled comparison: (1) develop an orientation-flexible framework integrating operational constraints with discrete box selection and cost optimization; (2) compare FFD and BF heuristics across cost efficiency, space utilization, and computational performance; and (3) quantify economic impacts of orientation flexibility relative to horizontal-only practices. Three packing strategies are evaluated: Orientation-flexible FFD, orientation-flexible BF, and a horizontal-only baseline representing current manual practice. All strategies process identical order

instances under identical constraints, enabling direct attribution of performance differences to algorithmic differences.

B. Case Context and Data Source

Empirical data derive from an operating e-commerce fulfillment company distributing personal care products (hair and scalp care). The operation processes high-volume orders containing multiple heterogeneous items with varying dimensions, weights, and levels of fragility. Packing decisions are constrained by dimensional weight-based pricing, in which transportation charges equal the greater of the actual weight or the volumetric weight (dimensional weight = volume/ δ , where $\delta = 5000 \text{ cm}^3/\text{kg}$). The operation utilizes four standardized box sizes: A ($14 \times 20 \times 6 \text{ cm}$, \$9), B ($17 \times 25 \times 9 \text{ cm}$, \$12), C ($20 \times 30 \times 11 \text{ cm}$, \$16), and D ($22 \times 35 \times 14 \text{ cm}$, \$20). Product catalog includes 8 SKUs with dimensions ranging 3.2-9.5 cm (length), 4.2-8.0 cm (width), 7.5-18.5 cm (height); weights 100-250g (average 213g, SD 58g); and fragility classifications distributed as 25% low (index 1-2), 50% medium (index 3), 25% high (index 4-5). This configuration reflects typical e-commerce fulfillment conditions, including order heterogeneity, discrete box catalogs, and dimensional weight pricing structures.

C. Mathematical Model and Problem Formulation

The three-dimensional bin packing problem with operational constraints is formulated as follows. Let $i \in I$ denote items in customer orders, where I is the total item count. Let $b \in B$ denote available box types. Let $k \in k_i$ denote feasible orientations for item i where $|k_i| = 6$ representing six possible three-dimensional rotations. Parameters include:

- (l_i, w_i, h_i) As original dimensions of item i ;
- (L_b, W_b, H_b) As internal dimensions of box b ;
- C_b As the packaging cost of box b ;
- f_i As fragility index of item i (dimensionless, higher values indicate greater fragility);
- m_i As mass of item;
- $\alpha = 0.80$ as the minimum base support ratio;
- δ As a dimensional weight divisor.

Objective Function: Minimize total logistics cost;

$$Z = \sum_{b \in B} (C_b + S_b)$$

where S_b represents shipping cost calculated via dimensional weight pricing.

$$S_b = \max \left(\sum_{i \in I_b} m_i, \frac{L_b \times W_b \times H_b}{\delta} \right)$$

This formulation captures the practical mechanism by which carriers charge based on either actual or volumetric weight, whichever is greater.

Constraints:

(1) Container Boundaries:

$$x_i + l'_{i,k} \leq L_b; y_i + w'_{i,k} \leq W_b; z_i + h'_{i,k} \leq H_b$$

where (x_i, y_i, z_i) denote placement coordinates and $(l'_{i,k}, w'_{i,k}, h'_{i,k})$ represent effective dimensions under orientation k .

(2) Non-Overlapping: Items $i \neq j$ in the same box must not occupy identical three-dimensional space, enforced via coordinate-based overlap checking.

(3) Fragility and Weight Precedence: To prevent product damage during handling and transportation, stacking decisions must respect both weight and fragility ordering. For item i placed above item j :

$$m_i \leq m_j \text{ and } f_i \leq f_j$$

This constraint ensures that heavier or more fragile items are not stacked on top of lighter or less fragile items.

(4) Base Support Stability: Stacking stability is further ensured through a minimum contact area constraint. Let A_{ij}^{contact} denote the contact area between item i (upper) and item j (lower), and let A_i^{base} denote the base area of item i . The following condition must hold:

$$\frac{A_{ij}^{\text{contact}}}{A_i^{\text{base}}} \geq \alpha \quad \text{where } \alpha = 0.80$$

This constraint ensures that at least 80% of an upper item's base area is supported by the item below.

D. Algorithm Selection Rationale

While recent literature explores deep reinforcement learning [22], [23] and exact methods including constraint programming and integer linear programming [29], [30], [31], this study focuses on classical constructive heuristics—First Fit Decreasing (FFD) and Best Fit (BF)—for three methodologically justified reasons.

Practical Deployability: Classical heuristics require no training data, hyperparameter tuning, or GPU acceleration. Deep reinforcement learning demands substantial training datasets and computational resources that may be unavailable in industrial e-commerce environments. Our focus on immediately deployable algorithms aligns with efforts to bridge theoretical optimization and practical fulfillment operations.

Computational Tractability: Exact methods (CP/IP) guarantee optimality but scale exponentially. Prior work shows CP/IP becomes prohibitive beyond 100-200 items [29], [30]. Our 600-order dataset (2-7 items per order) requires real-time solutions (<1 second for FFD, <5 seconds for BF). Exact methods would exceed these operational constraints by orders of magnitude.

Algorithmic Transparency: Deterministic heuristics provide clear decision paths facilitating operational debugging, quality assurance, and user trust. Warehouse

staff can trace decision logic and override when appropriate. Black-box approaches (neural networks, complex metaheuristics) obscure rationale, reducing operational acceptance where human workers retain final packing authority.

The traditional heuristic focus reflects a deliberate methodological decision prioritizing immediate industrial applicability, computational feasibility at scale, and operational transparency over algorithmic innovation.

E. Heuristic Packing Algorithms

First Fit Decreasing (FFD): Items are sorted in descending order by footprint area (length $\times$ width), with a secondary sort by weight and fragility. For each item, the algorithm sequentially attempts to place it in the smallest feasible box that satisfies all constraints. Upon finding the first feasible box-orientation combination, the algorithm accepts this placement without further evaluation. If no feasible placement exists across all boxes and orientations, the algorithm escalates to the next larger box size. Computational complexity is $O(n \log n)$ for sorting plus $O(nb)$ for placement, where n = items, b = box types. This efficiency enables real-time deployment in high-volume operations.

Best Fit (BF): The BF algorithm differs in its placement decision logic. For each item, all feasible box types and all feasible orientations are evaluated. The algorithm then selects the box-orientation combination that minimizes residual void volume in the packed box:

$$V_{void} = (L_{box} \times W_{box} \times H_{box}) - \sum (l'_{i,k} \times w'_{i,k} \times h'_{i,k})$$

By minimizing void space, the BF algorithm typically achieves higher space utilization than the FFD algorithm. This exhaustive evaluation typically achieves superior space utilization at substantially higher computational cost $O(nb \times 6)$ per item, where 6 represents orientation permutations.

Baseline (Horizontal-Only): The baseline strategy constrains all items to a single horizontal orientation (zero rotation) and selects the smallest box using the same greedy logic as FFD. All four

constraint categories are validated in the same way as the orientation-flexible strategies. Computational complexity is $O(nb)$. The baseline was simulated using the same framework as FFD and BF, ensuring that performance differences are attributable solely to orientation flexibility.

Fig. 1 and 2 illustrate the FFD and BF algorithmic workflows. FFD accepts the first feasible box-orientation combination, while BF evaluates all combinations and selects the one minimizing residual void volume. Both algorithms apply the same four constraint checks and escalate to the next larger box when placement fails.

F. Simulation Implementation

Fig. 3 illustrates the overall simulation workflow, consisting of six phases: input data loading, order-level processing across three strategies, packing with constraint validation, performance measurement, model validation, and output generation.

The computational model was implemented in Python 3.10 using Google Colaboratory (Colab), a cloud-based Jupyter notebook environment. Colab provides pre-installed scientific computing libraries, including Pandas for data manipulation, NumPy for numerical computation [34], Matplotlib for visualization [35], and Seaborn for statistical graphics [36]. The architecture employs a modular design with separate modules for constraint validation, box selection, item placement, and metric calculation. At each placement attempt, algorithms validate four constraint categories: (1) container boundaries ensuring items fit within box dimensions; (2) non-overlapping, verifying distinct items occupy separate spatial regions; (3) fragility and weight precedence maintaining safe stacking order; and (4) base support ensuring adequate stability. If constraint violations occur, algorithms increase the box size and retry placement. The simulation processes customer orders sequentially, applying designated algorithms to each order independently. Post-packing, performance metrics including total logistics cost, void volume, dunnage requirements, and computational runtime are calculated and recorded.

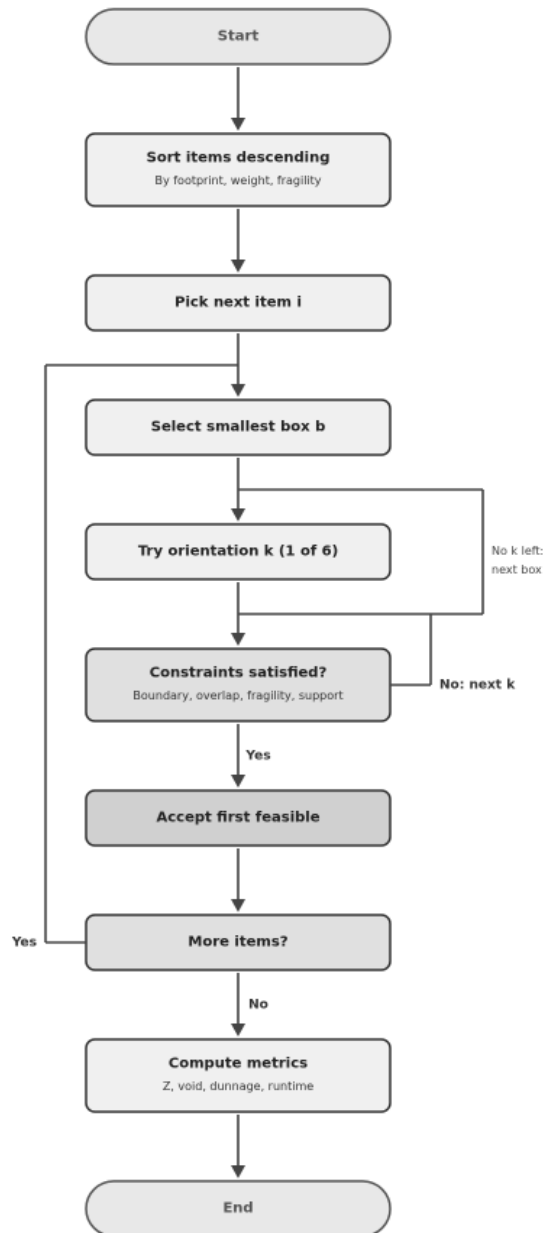


Fig. 1. Flowchart of the FFD algorithm. Items are sorted by footprint area (descending), then the first feasible box-orientation combination is accepted. Complexity: $O(n \log n)$ plus $O(nb)$.

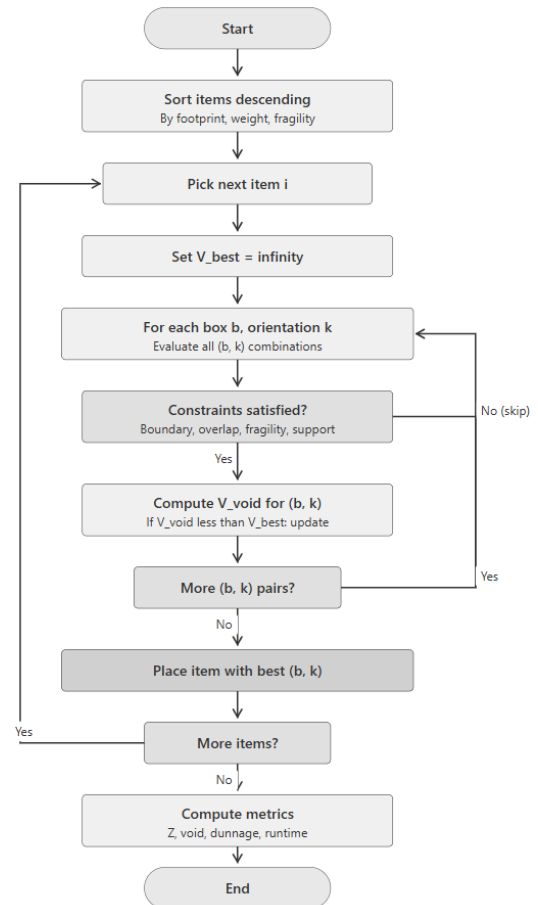


Fig. 2. Flowchart of the BF algorithm. All feasible box-orientation combinations are evaluated for each item, selecting the one that minimizes residual void volume. Complexity: $O(nb \times 6)$ per item.

G. Experimental Dataset

The framework was evaluated using 600 customer orders, each containing 2-7 items selected from the 8-SKU catalog. Orders reflect realistic e-commerce characteristics, including dimensional variation, weight distribution, and heterogeneity in fragility. All experiments used identical predefined box sizes to ensure comparability. Although the framework is generic, input parameters, item dimensions, weights, fragility indices, and order compositions are derived from operational data, thereby strengthening external validity and ensuring findings reflect realistic fulfillment behavior rather than idealized scenarios.

H. Performance Evaluation Metrics

Algorithm performance is evaluated through four metrics capturing economic efficiency, space utilization, and computational feasibility: (1) Total Logistics Cost (Z): Sum of packaging material costs and transportation charges representing primary economic metric enabling bottom-line financial impact comparison; (2) Void Space Volume (V_{void}): aggregate unused volume across boxes quantifying geometric efficiency; (3) Dunnage Material Cost: estimated cost of protective padding required for product safety reflecting trade-off between tight packing and adequate protection; and (4) Average Computational Runtime: CPU execution time per order measured in milliseconds capturing implementation feasibility for real-time deployment. These metrics provide a multidimensional evaluation considering solution quality, cost efficiency, and practical deployment constraints.

First, solution stability was evaluated using five-fold stratified cross-validation. The 600-order dataset was partitioned into five approximately equal subsets, stratified by order size to preserve heterogeneous order characteristics across folds. Each packing strategy is applied independently to all folds. One-way Analysis of Variance (ANOVA) was applied within each strategy to test whether mean performance metrics differed across folds.

Second, robustness to parameter uncertainty was assessed through One-At-A-Time (OAT) sensitivity analysis. Three key operational parameters were systematically varied while holding others constant: (i) the base support ratio (α), (ii) the dimensional weight divisor (δ), and (iii) box cost levels. Performance sensitivity was assessed based on total logistics cost, void space, dunnage requirements, and computational runtime.

IV. RESULTS

A. Experimental Dataset and Simulation Setup

The experimental dataset comprises 600 customer orders drawn from real operational data in the personal care products sector. Each order contains 2 to 7 items, with an average of 4.17 items per order, selected from a catalog of 8 SKUs. The products exhibit heterogeneous physical characteristics, including variations in dimensions, weight, and fragility levels, thereby reflecting realistic e-commerce fulfillment conditions.

For all experiments, a standardized set of four discrete box sizes commonly employed in e-commerce operations was used: A ($14 \times 20 \times 6$ cm), B ($17 \times 25 \times 9$ cm), C ($20 \times 30 \times 11$ cm), and D ($22 \times 35 \times 14$ cm). A dimensional weight divisor of $= 5000 \text{ cm}^3/\text{kg}$ and a minimum base support ratio of $= 0.80$ were applied consistently across all strategies. To ensure strict comparability, each packing algorithm processed the same sequence of order instances under identical operational constraints.

B. Comparative Performance Analysis

Table I presents comprehensive performance comparisons across three packing strategies: Baseline (horizontal-only manual rule), FFD (First Fit Decreasing with orientation flexibility), and BF (Best Fit with orientation flexibility). Results represent deterministic outcomes from simulation across all 600 orders. All baseline results were generated through the same simulation framework as FFD and BF, applying the manual rule logic (horizontal-only, smallest-box-first) programmatically to ensure controlled comparison.

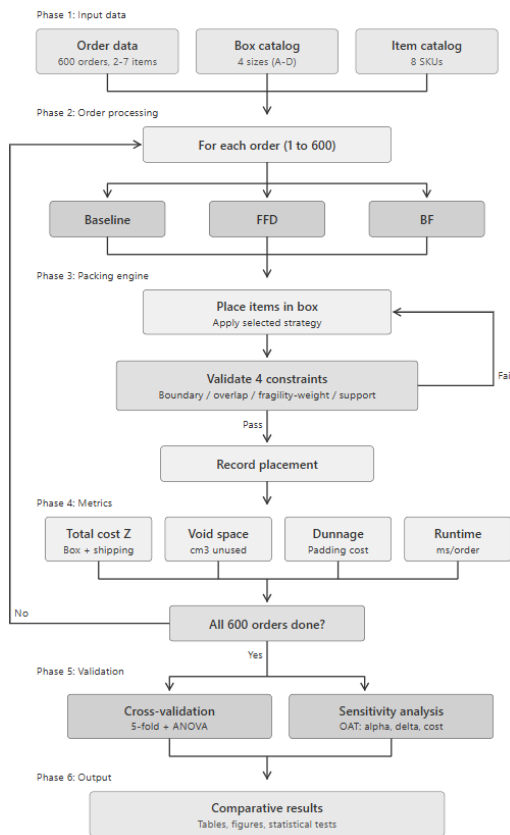


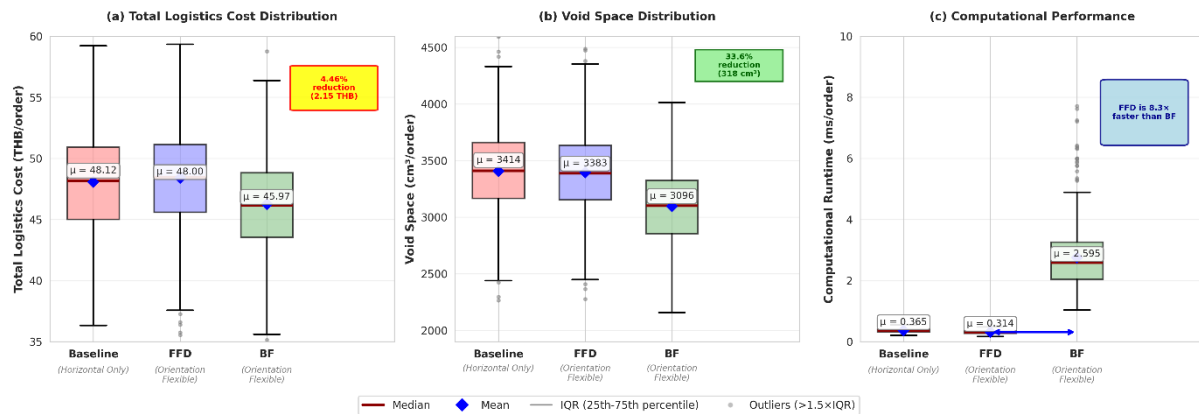
Fig. 3. Flowchart of the simulation process. The pipeline processes 600 orders through three packing strategies (Baseline, FFD, BF) under identical constraints, computes performance metrics, and validates results through cross-validation and sensitivity analysis.

I. Model Validation Procedures

To assess the reliability and robustness of the proposed packing optimization framework, two complementary validation procedures were employed: cross-validation and sensitivity analysis.

TABLE I
AVERAGE PERFORMANCE PER ORDER (N = 600)

Metric	Baseline	FFD	BF
Total Logistics Cost, Z (THB/Order)	48.12	48.00	45.97
Void Space (cm ³ /Order)	3,413.56	3,383.24	3,095.91
Dunnage Cost (THB/Order)	1.707	1.692	1.548
Runtime (ms/Order)	0.365	0.314	2.595



Note: Distributions based on simulation results. Whiskers extend to 1.5xIQR. Outliers shown as individual points. BF runtime variability reflects exhaustive evaluation in complex orders. ANOVA confirms no significant differences across 5-fold cross-validation (all $p > 0.05$).

Fig. 4. Performance distributions across 600 orders for Baseline (horizontal-only), FFD, and BF strategies: (a) total logistics cost, (b) void space, and (c) computational runtime. BF achieves a 4.4% cost reduction and a 33.6% reduction in void space relative to the Baseline. FFD is 8× faster than BF but yields only a minimal cost improvement

As shown in Table I, the results clearly demonstrate that orientation flexibility significantly improves in both economic and spatial performance relative to the horizontal-only baseline. Among the evaluated strategies, BF consistently achieves the lowest logistics cost, void space, and dunnage consumption per order. On average, BF reduces logistics costs by approximately 2.14 THB per order (4.4%) relative to the baseline. FFD also improves upon the baseline, though to a lesser extent. While FFD benefits from flexible orientation, it's greedy.

The acceptance rule limits its ability to fully exploit the available box capacity, resulting in performance outcomes that remain closer to Baseline than to BF in terms of cost and space utilization.

C. System-Level Economic Impact

To evaluate the operational significance of these improvements, Table II reports cumulative. Performance metrics aggregated across all 60 orders.

TABLE II
AGGREGATE PERFORMANCE ACROSS 600

Metric	Baseline	FFD	BF
Total Z (THB)	28,869.48	28,798.30	27,583.20
Total Void (cm ³)	2,048,133.14	2,029,943.14	1,857,543.14

At the system level, the economic benefits of BF become more pronounced. Relative to Baseline, BF achieves a total logistics cost reduction of 1,286.28 THB across 600 orders, accompanied by a reduction of approximately 190,590 cm³ in unused box volume and a decrease of more than 95 units in dunnage material consumption. Although BF incurs a higher computational cost, its total runtime remains within a feasible range for batch-based fulfillment planning. FFD yields only modest aggregate savings relative to Baseline, indicating that orientation flexibility alone is insufficient to generate substantial system-level benefits without an informed box-selection mechanism.

D. Decomposition of Performance Improvements

Table III summarizes the incremental gains of FFD_OF and BF_OF relative to the baseline. These results indicate that the dominant driver of cost reduction is improved space utilization rather than algorithmic overhead. The substantial reduction in Lower-dimensional-weight charges and the reduced need for protective dunnage. In contrast, FFD_OF yields only a marginal reduction in void, which explains its limited cost advantage. The void space under BF_OF directly translates into

TABLE III
PERFORMANCE DIFFERENCES RELATIVE TO BASELINE

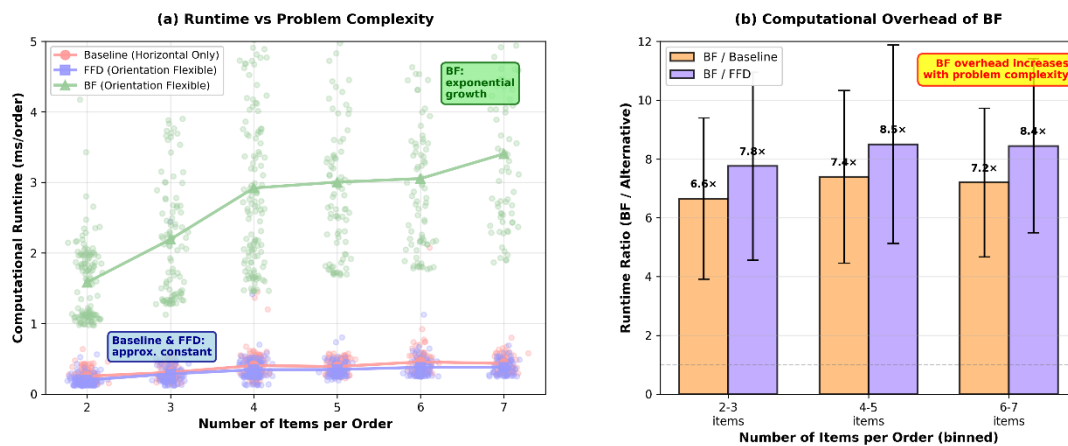
Metric	Baseline	FFD	BF
ΔZ (THB)	0	-71.18	-1,286.28
ΔVoid (cm ³)	0	-18,190	-190,590
$\Delta \text{Dunnage}$	0	-9.10	-95.30
Runtime (ms/Order)	0.365	0.314	2.595

E. Packing Efficiency, Computational Trade-offs, and Operational Implications

The experimental results show that improvements in packing efficiency arise from the interaction between geometric flexibility and box-selection logic, rather than from orientation flexibility alone. Allowing item rotation increases available packing space and enables configurations unattainable under horizontal-only constraints, resulting in substantial reductions in void space. However, the degree to which this expanded feasibility space translates into economic and spatial benefits depends critically on the algorithm's selection criterion.

While both FFD and BF utilize orientation flexibility, BF further exploits this flexibility by systematically evaluating alternative box-orientation combinations and selecting configurations that minimize residual void volume. As a result, BF achieves the largest reductions in void space and associated logistics costs. In contrast, FFD, which accepts the first feasible placement, captures only a portion of the potential gains, indicating that orientation flexibility is necessary but not sufficient to maximize packing efficiency.

These efficiency gains must be interpreted in the context of computational performance. A clear trade-off emerges between solution quality and runtime. FFD offers the fastest execution, processing orders approximately eight times faster than BF, making it well-suited for high-throughput environments with strict latency requirements. BF, while computationally more demanding, maintains average runtimes at the millisecond level, which remain acceptable for batch-oriented or cost-sensitive fulfillment operations.



Note: Individual points show order-level measurements; lines connect mean values. Whiskers extend to $1.5 \times \text{IQR}$. BF exhibits exponential runtime growth with order complexity, while Baseline and FFD remain approximately constant across all problem sizes.

Fig. 5. Computational Scaling Analysis Across Problem Sizes. (a) Runtime vs problem complexity (b) Computational overhead of BF

Fig. 5 illustrates computational scaling behavior across problem sizes ranging from 2 to 7 items per order. As shown in Fig. 5a, BF runtime increases exponentially with increasing order complexity, rising from 1.58 ms for 2-item orders to 3.41 ms for 7-item orders. In contrast, both Baseline and FFD strategies maintain approximately constant runtime (0.26-0.46 ms and 0.20-0.38 ms, respectively) across all order sizes examined. Despite their theoretical complexities being $O(n \log n)$ for sorting, $O(nb)$ for FFD, and $O(nb)$ for Baseline, the limited range of order sizes in this dataset (2-7 items) means the growth factor is negligible in practice. The difference between sorting 2 items and 7 items is negligible at the millisecond scale. This consistent observation suggests that the computational cost of Baseline and FFD is practically

unaffected by order complexity, given typical e-commerce order sizes. This supports their use in real-time systems.

Fig. 5b quantifies this computational disadvantage through runtime ratios. BF is consistently 6.6-7.2 $\times$ slower than Baseline and 7.6-8.5 $\times$ slower than FFD across all order-size bins. Notably, this overhead increases slightly with problem complexity: For 2-3-item orders, BF is 6.6 $\times$ slower than Baseline, increasing to 7.2 $\times$ for 6-7-item orders. This pattern confirms that BF's exhaustive orientation-evaluation approach becomes increasingly costly as the solution space expands.

These results have significant operational implications. For warehouses mainly handling small orders (≤ 4 items), BF's 2-3 ms overhead may be

acceptable if cost optimization is paramount. However, for facilities handling larger orders or requiring high throughput (>100 orders/hour), FFD's superior computational efficiency becomes critical, enabling real-time packing decisions without increasing costs.

These findings indicate that both orientation-flexible strategies are operationally viable; however, the choice of strategy depends on organizational priorities. Systems emphasizing responsiveness and throughput may prefer FFD, while operations focusing on cost reduction and material efficiency may benefit more from BF. This integrated perspective emphasizes that packing performance, computational feasibility, and operational objectives must be jointly considered when deploying algorithmic packing solutions in real-world e-commerce fulfillment systems.

F. Model Validation Results

This section reports the results of the model validation procedures, including cross-validation and sensitivity analysis, to evaluate the stability and robustness of the proposed packing optimization framework.

Cross-Validation Results

To examine solution stability, the 600-order dataset was divided into five stratified folds of approximately equal size. Each packing strategy was evaluated independently on all folds, and order-level performance metrics, including total logistics cost (Z), void space, and computational runtime, were recorded.

One-way Analysis of Variance (ANOVA) was performed for each strategy to test whether mean performance differed significantly across folds. The results show no statistically significant differences across subsets for any strategy or performance metric (all p-values > 0.05). Specifically, p-values ranged from approximately 0.62 to 0.99 across total logistics cost, void space, and runtime. The consistently low F-statistics suggest that between-fold variability is negligible relative to within-fold variability. These findings confirm that the observed performance outcomes are not attributable to specific subsets of customer orders, but rather reflect stable algorithmic behavior under heterogeneous order compositions.

Constraint Feasibility Validation: All 600 orders achieved feasible packing solutions under the three strategies (Baseline, FFD, BF) at baseline constraint settings ($\alpha=0.80$, fragility-based orientation restrictions, weight precedence enforcement). Post-solution verification confirmed 100% compliance with operational constraints: Fragile items were placed upright, weight precedence was maintained (no light items supporting heavier items), and base support ratios exceeded the 80% threshold across all solutions. This high feasibility rate indicates that the constraint severity strikes an appropriate balance: Strict enough to ensure operational safety yet permissive enough to maintain algorithmic tractability, without requiring manual intervention or constraint relaxation.

Sensitivity Analysis Results

Sensitivity analysis was conducted using a One-At-A-Time (OAT) approach to assess robustness to key operational parameters.

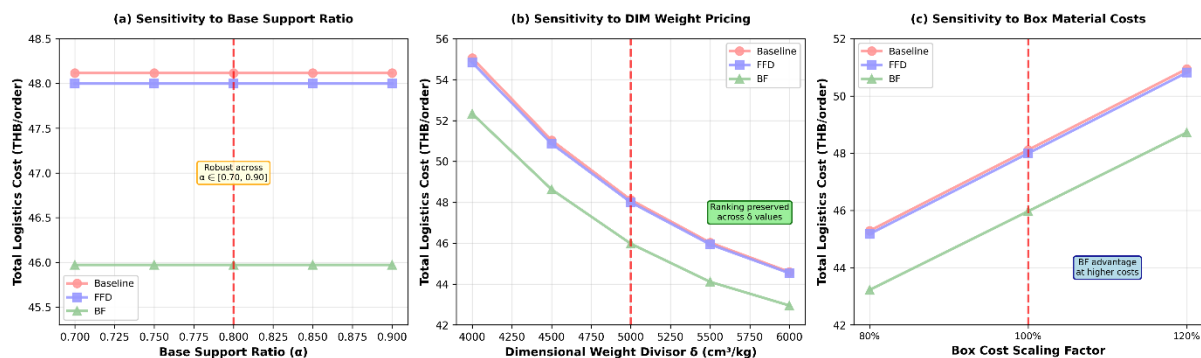


Fig. 6. Sensitivity analysis showing robustness to operational parameter variations: (a) base support ratio α , (b) dimensional weight divisor δ , and (c) box material costs. Relative performance ranking (BF > FFD > Baseline) is preserved across all parameter ranges, confirming framework robustness.

Sensitivity to Base Support Ratio (α)

Fig. 6a examines sensitivity to the base support ratio (α), which governs minimum contact area requirements for fragile item placement. Across the range $\alpha \in [0.70, 0.90]$ ($\pm 12.5\%$ of baseline $\alpha = 0.80$), all three strategies exhibit perfect stability with zero cost variation. Specifically, Baseline maintains 48.12 THB/order, FFD maintains 48.00 THB/order, and BF maintains 45.97 THB/order across all five α values tested. This remarkable invariance indicates that the framework's performance is independent of the strictness of constraints within plausible operational ranges. The consistent 2.15 THB/order gap between BF and Baseline confirms that strategic superiority persists regardless of whether facilities adopt conservative ($\alpha = 0.85-0.90$) or moderate ($\alpha = 0.70-0.75$) fragility protection policies. This outcome challenges the common assumption that tighter operational constraints necessarily reduce solution quality and demonstrates that our constraint-aware packing logic maintains efficiency without incurring performance penalties.

Sensitivity to Dimensional Weight Divisor (δ)

Sensitivity to dimensional weight pricing, as shown in Fig. 6b, assesses the robustness variations in carrier policy. Across δ values ranging from 4000 to 6000 cm^3/kg ($\pm 20\%$ of baseline $\delta = 5000$), all strategies exhibit expected linear response. At $\delta = 4000$ (high-dimensional weight penalty), costs reach 55.05 THB/order for Baseline, 54.83 THB/order for FFD, and 52.33 THB/order for BF, representing a 14.4% increase relative to baseline costs due to heightened volumetric charges. At $\delta = 6000$ (low penalty), costs decrease to 44.59 THB/order (Baseline), 44.53 THB/order (FFD), and 42.95 THB/order (BF), a 7.4% reduction. Critically, the relative ranking (BF > FFD > Baseline) remains unchanged throughout this range, with BF maintaining a consistent 2.1-2.7 THB/order advantage over Baseline. The linear relationship between δ and total cost ($R^2 > 0.99$ across all strategies) enables straightforward cost projections under varying carrier agreements, facilitating informed carrier selection and contract negotiation.

Sensitivity to Box Cost Scaling

Fig. 6c examines sensitivity to changes in box material cost by evaluating scenarios at 80%, 100%, and 120% of the baseline packaging cost. At 80% baseline, total logistics costs are 45.29 THB/order (baseline), 45.18 THB/order (FFD), and 43.22 THB/order (BF), yielding a BF cost advantage of 2.07 THB/order (4.57%) over baseline. At 100% baseline costs, this advantage is 2.14 THB/order (4.45%). At 120% costs, the advantage increases to 2.22 THB/order (4.36%), a 7.2% increase in absolute savings relative to the 80% scenario. This amplification pattern provides an important operational insight: BF's void reduction capabilities become increasingly

valuable in absolute terms when packaging materials are expensive, even though the percentage advantage remains relatively stable (4.36-4.57%). This finding provides a practical decision criterion: Facilities facing premium packaging costs ($\geq 110\%$ of the baseline) realize greater absolute per-order savings from BF implementation and should prioritize this strategy, while facilities with discounted materials ($< 90\%$ of the baseline) may find FFD's superior computational efficiency sufficient for their cost structure.

Collectively, these sensitivity analyses demonstrate three key properties of the framework. First, constraint-invariant performance (Fig. 6a) validates the consistency of recommendations across facilities with different safety requirements. Second, predictable linear responses to pricing variations (Fig. 6b) enable reliable cost forecasting under diverse carrier policies. Third, value amplification at premium costs (Fig. 6c) provides actionable guidance for context-dependent strategy selection. The preservation of relative performance rankings (BF > FFD > Baseline) across all parameter combinations confirms that the framework maintains robust performance across diverse e-commerce operating conditions without requiring extensive recalibration.

V. DISCUSSION

The findings reveal that orientation flexibility is a primary driver of packing efficiency improvements, in packing efficiency enabling algorithms to exploit configurations inaccessible under horizontal-only constraints, as noted in [9]. This flexibility yields a substantial reduction in void space, directly lowers dimensional-weight charges, and dunnage requirements. Importantly, economic benefits derive primarily from geometric efficiency rather than algorithmic sophistication, as cost reductions are closely tied to spatial compaction, indicating that geometric exploitation is the dominant mechanism driving savings in dimensional-weight-based pricing environments [37] where inappropriate box selection and item placement lead to higher logistics costs, wasted space, and reduced sustainability. This study aims to minimize the number of boxes used per order while improving space utilization by formulating the problem as a 3D Bin Packing Problem (3D-BPP).

A comparative analysis reveals a divergence between first-fit and best-fit heuristics when orientation flexibility is present. While both outperform baselines, best-fit consistently achieves superior outcomes by explicitly minimizing residual void via exhaustive evaluation of box-orientation combinations. However, this advantage diminishes in highly constrained solution spaces with limited box catalogs, where greedy heuristics may approximate optimal solutions reasonably well. This convergence

highlights structural properties of discrete packaging environments where catalog limitations naturally bound combinatorial complexity.

Results demonstrate clear trade-offs between solution quality and computational efficiency. Best-fit with orientation flexibility achieves the greatest economic and spatial efficiency but requires longer computation time, while first-fit offers near-baseline speed with moderate gains. Crucially, even intensive strategies operate within millisecond-level runtimes, reframing the trade-off from feasibility versus infeasibility to degrees of optimization. This enables heuristic selection tailored to operational priorities without compromising real-world deployability.

Integration of operational safety constraints, fragility protection, weight precedence, and base support imposes only marginal performance penalties. The constrained framework eliminates all safety violations at minimal cost and minimal increase in void space, demonstrating that operational realism and optimization performance are not mutually exclusive. This challenges assumptions that practical constraints necessarily degrade solution quality and underscores the value of embedding domain knowledge directly into decision logic.

From a managerial perspective, substantial cost savings can be achieved through modest changes in packing logic. For high-volume fulfillment centers, small per-order savings add up to significant annual reductions, while reduced dunnage usage yields secondary benefits, including lower material costs, reduced packing labor, and improved sustainability. Different strategies suit different contexts: first-fit with orientation flexibility is optimal for high-throughput environments with stringent latency requirements, while best-fit is preferable in cost-sensitive operations where computation time is justified by greater savings. Managers can therefore adopt context-dependent strategy selection rather than universal solutions.

The observed migration toward smaller boxes under orientation-flexible strategies highlights interactions between algorithm design and packaging policy. Expanding box catalogs may amplify best-fit benefits by increasing the granularity of choice, suggesting that investments in algorithmic optimization and packaging design should be considered jointly. More diverse catalogs unlock additional value from advanced heuristics, while improved heuristics increase the utilization efficiency of existing assets.

Millisecond-level runtimes indicate compatibility with real-world fulfillment systems, and modular design facilitates integration into existing warehouse or order management systems without extensive infrastructure changes. Framework robustness to data partitioning and parameter variations enables reliable deployment across diverse demand patterns and operating conditions. These findings collectively

demonstrate that orientation flexibility, when combined with informed box selection and realistic operational constraints, yields meaningful improvements in e-commerce packing efficiency, providing both theoretical insight into discrete packing problems and actionable guidance for balancing cost, efficiency, and operational safety.

VI. CONCLUSION

This study proposed and evaluated an orientation-flexible packing optimization framework integrating realistic operational constraints with discrete box selection and cost minimization. Using simulation-based experiments on 600 real-world e-commerce orders, the framework systematically compared a horizontal-only baseline with two orientation-flexible heuristics: First Fit Decreasing and Best Fit. Results demonstrate that orientation flexibility significantly improves packing efficiency across economic, spatial, and material dimensions, consistently reducing total logistics cost, void space, and dunnage consumption. Best Fit achieves the greatest overall efficiency, while First Fit offers a favorable balance between gains and computational speed. Integration of operational safety constraints, fragility protection, weight precedence, and base support eliminates unsafe configurations with only marginal performance penalties, confirming that practical requirements and optimization objectives can be aligned within unified algorithmic frameworks. Cross-validation and sensitivity analyses confirm robustness across heterogeneous order subsets and logical responses to parameter variations, including support thresholds, carrier pricing, and box costs, establishing practical viability and generalizability for real-world fulfillment operations.

Despite contributions, several limitations warrant acknowledgment. The experimental setting relies on a discrete catalog of four predefined box sizes; while reflecting common practice, more granular assortments may alter the relative performance of heuristics, particularly the best-fit advantage. The packing model employs approximate height-map-based support evaluation rather than full three-dimensional contact mechanics, which may not capture complex interactions from irregular geometries or deformable materials. Simulations assume deterministic item dimensions, weights, and fragility indices derived from historical data, yet measurement uncertainty, packaging tolerances, and handling variability introduce deviations not explicitly modeled. Computational experiments were conducted in single-threaded Python environments; while runtimes proved sufficient for deployment, alternative implementations or hardware configurations could affect scalability and real-time applicability.

Several research avenues emerge from this work. Extending the framework to larger, more diverse box catalogs could illuminate how packaging assortment design interacts with heuristic selection, with joint optimization of box assortment and packing strategy representing promising directions. Future studies may incorporate detailed physical modeling, including partial material deformability, irregular item shapes, or stochastic stability constraints to enhance realism when product geometry deviates from cuboid assumptions. Integrating dynamic order arrival with real-time decision-making would enable evaluation in streaming or online fulfillment environments, using hybrid approaches that combine fast heuristics with periodic optimization-based refinement to balance solution quality and responsiveness. Finally, future research may explore broader sustainability objectives, including carbon emissions, material recyclability, and reverse logistics, and embed environmental performance metrics alongside economic objectives to align packing optimization with emerging sustainability goals in e-commerce logistics.

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