Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AF07.20260074
Published: May 13, 2026

AI-Driven Slotting Strategies and Picking Productivity in Distribution Centres: A Systematic Review

Malcolm Smith, Mia Mangaroo-Pillay and Vanya Jansen
Department of Industrial Engineering
Stellenbosch University, South Africa
23544546@sun.ac.za, miamangaroopillay@sun.ac.za, vanya@sun.ac.za

Abstract

Order picking is a labour-intensive activity in distribution centres, making slotting decisions critical for productivity. Slotting is often managed reactively and without consistent metrics for performance quantification. This study presents a systematic literature review (SLR) that examines how the impact of slotting strategies on picking productivity can be quantified and how artificial intelligence (AI) can enable a transition toward proactive and dynamic slotting optimisation. Following a structured SLR, literature published between 2020 and 2026 was retrieved from Scopus, Web of Science, and IEEE Xplore, resulting in 27 eligible studies for analysis. The findings indicate that effective SKU placement consistently reduces picker travel distance and picking time while improving throughput and order fulfilment performance, with reported productivity gains exceeding 60% in some literature. The review further reveals a transition toward AI-driven slotting approaches, integrating demand forecasting, optimisation algorithms, and simulation techniques to support proactive decision-making. By consolidating quantifiable performance metrics and AI-enabled methods, this study provides a structured approach to give real-world insights into slotting techniques and evaluations and predictive optimisation, highlighting key opportunities for possible future implementations and validation.

Keywords
Predictive slotting, SKU allocation, Order picking productivity, Artificial Intelligence, Systematic Literature Review.

1. Introduction
Order picking is widely recognised as a labour-intensive activity in distribution centre (DC) planning, with picker travel often accounting for the largest share of total picking time (De Koster et al., 2007). As a result, slotting, the strategic assignment of SKUs to storage and picking locations, impacts travel distance, congestion levels, stock replenishment, and ergonomic risk within distribution centres, directly impacting productivity within a DC (Gu, Goetschalckx and McGinnis, 2010). Despite its operational significance, slotting in many DCs is still managed as an ad-hoc and reactive task rather than as a proactive, performance and data-driven improvement framework supported by quantifiable metrics. For organisations managing thousands of SKUs, particularly in the Fast Moving Consumer Goods (FMCG) industry, in a complex order fulfilment environments, two practical challenges arise: first, how to quantify the productivity impact of slotting interventions using credible and quantifiable metrics; and second, how to transition from periodic, ad-hoc reslotting towards proactive, data-driven, and potentially AI-enabled dynamic slotting strategies capable of responding to future demand patterns (Wu and Chen, 2022).

1.1 Aim of Study
This study takes the form of a systematic literature review (SLR) and aims to examine how the impact of slotting on distribution centre picking productivity can be quantified and to investigate how data-driven forecasting and

optimisation, including artificial intelligence, supports the transition from reactive slotting practices toward proactive and dynamic slotting optimisation.

2. Methodology

In order to achieve the aim, a systematic literature review (SLR) was conducted to collect data. This took the form of a scoping SLR, which allowed for the investigation of the definitions, benefits, barriers, and enablers of using slotting to quantify productivity impacts in distribution centers, as well as current AI-driven slotting techniques to promote and optimize proactive slotting. This followed the SLR method proposed by Albliwi et. Al. which is detailed in the steps and sections that follow (Albliwi et al., 2014):

- **Step 1: Develop a research purpose and/or objective** – Clearly state the aim of the SLR
- **Step 2: Develop research protocol** – Develop a research protocol that establishes the purpose, inclusion criteria, exclusion criteria, databases, search, and quality assessment criteria of the study
- **Step 3: Establish relevance criteria** – State a general reasoning if a resource is relevant to this study
- **Step 4: Search and retrieve the literature** – Conduct searches using scientific databases to find literature
- **Step 5: Selection of studies** – Use the inclusion and exclusion criteria to select studies
- **Step 6: Quality assessment for relevant studies** – Assess the quality of each paper
- **Step 7: Data extraction** – Extract relevant information
- **Step 8: Analysis and synthesis of findings** – Analyse and synthesise the data from the documents
- **Step 9: Report** – Report the review in detailed results
- **Step 10: Dissemination** – Publish the SLR

2.1 Step 1 – Develop research purpose

The purpose of this study is to systematically evaluate and document how DC slotting strategies influence order-picking productivity and to explore how advanced analytics and artificial intelligence can enable a transition from reactive, ad-hoc slotting practices to proactive, data-driven optimisation. Through a systematic literature review, the study aims to identify measurable productivity impacts, key operational drivers of slotting performance, and emerging predictive approaches that support dynamic SKU placement.

2.2 Step 2 – Develop research protocol

A research protocol was developed, as depicted in Table 1.

Table 1. Research Review Protocol

Purpose of the study	• This study aims to evaluate how warehouse slotting strategies impact order-picking productivity and operational performance. It systematically reviews existing research to identify measurable productivity gains and the key factors influencing slotting effectiveness. The study also explores how artificial intelligence and advanced analytics can enable proactive, predictive slotting optimisation in distribution centers.
Inclusion criteria	• Literature that contains the relevant search terms in the title, abstract, or keywords • Literature that discusses measurable productivity impacts of slotting in a distribution center • Literature that discusses how AI can enable and optimise proactive slotting techniques.
Exclusion Criteria	• Non-English studies • Studies published before 2020 • Non-Scientific studies
Search databases	• Scopus • Web Of Science • IEEE Xplorer

Search strings	• ("slotting" OR "storage assignment" OR "warehouse assignment" OR "SKU allocation" OR "pick face assignment" AND "warehouse" OR "distribution center*" OR "distribution centre*" AND "pick* productivity" OR "order pick*" OR "pick* efficiency" OR "pick* performance" OR "productivity gains" OR "efficiency gains" AND "fast moving consumer goods" OR "FMCG") • ("slotting" OR "storage assignment" OR "warehouse assignment" OR "SKU allocation" OR "pick face assignment" AND "warehouse" OR "distribution center*" OR "distribution centre*" AND "pick* productivity" OR "pick* efficiency" OR "pick* performance" OR "productivity gains" OR "efficiency gains" AND "fast moving consumer goods" OR "FMCG" AND "artificial intelligence")
Quality assessment criteria	• All duplicate literature must be removed • Literature must be relevant • Studies must be scientific • Studies must have appropriate data collection techniques

2.3 Step 3 – Establish relevance criteria
The study is relevant if slotting and SKU placement decisions are linked to outcomes that influence and can quantify picking performance and picker productivity, and in addition discusses how dynamic and predictive slotting can be incorporated using artificial intelligence.

2.4 Step 4 – Search and retrieve the literature
During Step 4, literature search and retrieval were carried out using the databases specified in Table 1, yielding a total of 539 papers. The identification phase in Figure 1 presents the detailed breakdown of records obtained during this stage.

2.5 Step 5 – Selection of studies
The papers retrieved from the IEEE Xplore database were analysed to determine whether the relevant search strings appeared within the title, abstract, or keywords. The initial search strings for the IEEE Xplore database yielded 514 papers but were further refined and resulted in 77 documents that had the keywords in the title, abstract and keywords. Duplicate records and retraction notices were removed from the initial results. Following this screening stage, 78 papers met the inclusion criteria, as illustrated in the screening section of Figure 2. Of these, seven papers were inaccessible, resulting in 71 studies proceeding to the next phase of review.

During the exclusion process, several studies were removed because they did not explicitly address the impact of SKU allocation; instead, they focused primarily on picker routing optimisation or broader supply-chain routing rather than operations within a distribution centre. After applying these criteria, a total of 27 papers were deemed eligible for inclusion in the review, as indicated in the eligibility section of Figure 1.

2.6 Step 6 – Quality assessment for relevant studies
All 27 studies were evaluated against the quality assessment criteria outlined in Table 1, and each met the required standards for inclusion in the systematic literature review, as shown in Figure 1.

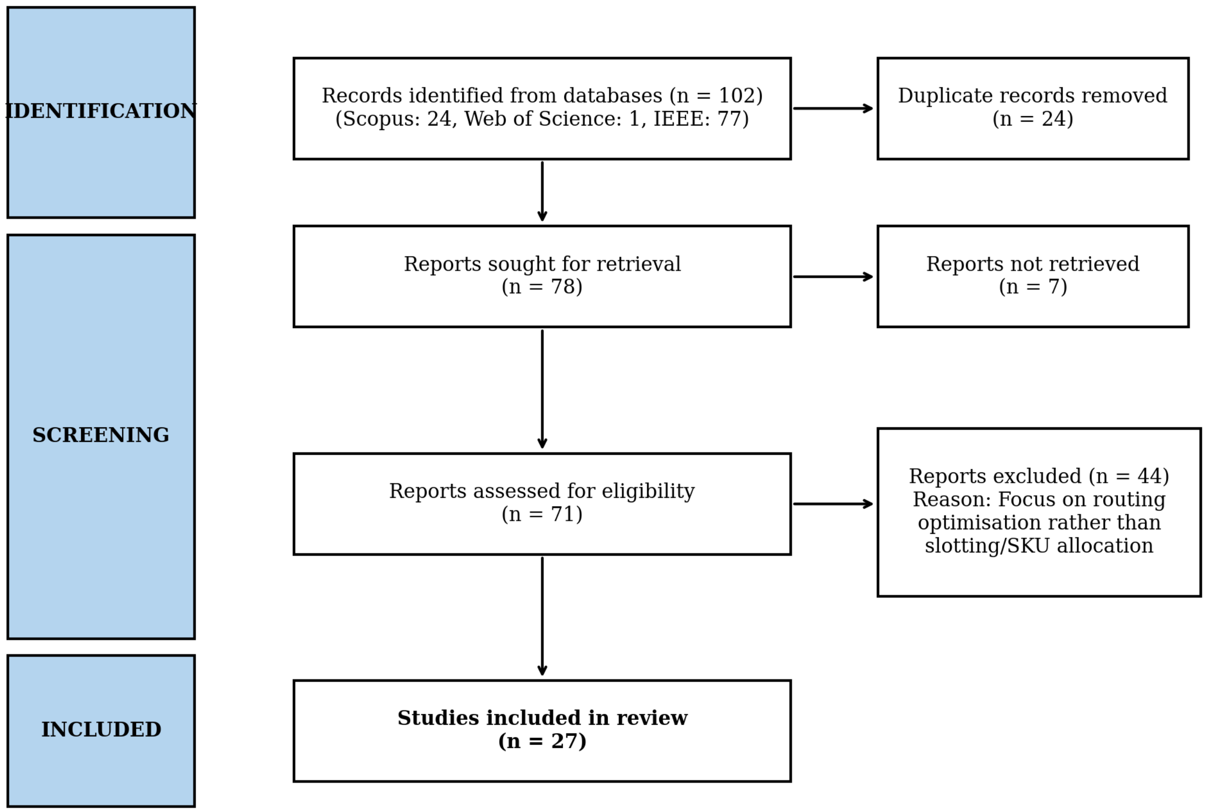

Figure 1. Selection process chart (Adapted from PRISMA guidelines)

3. Results and Discussion

The findings derived from Steps 7 and 8 of the SLR methodology are presented and discussed in the following sub-sections.

3.1 Step 7 – Data extraction

After finalising the list of studies for inclusion, the full texts were reviewed in detail, and the relevant data were extracted. It should be noted that the SLR was intentionally restricted to research conducted between 2020 and 2026 to ensure relevance, and the scope was further narrowed to studies focusing on fast-moving consumer goods (FMCG) distribution centre environments, where possible

The findings indicate that most studies investigated slotting strategies and SKU allocation techniques aimed at improving order-picking productivity, while an emerging subset explored how artificial intelligence can enable a transition from reactive slotting approaches towards more proactive and predictive decision-making. Although the industry scope was defined, the results reveal that research remains unevenly distributed across different operational contexts, highlighting opportunities for future work to further investigate AI-enabled proactive slotting within the FMCG supply chain. The studies included in the review can be found in Appendix A.

3.2 Step 8 – Analysis and synthesis of findings

Following the full-text review, the relevant data were extracted, analysed, and synthesised, with the findings presented in the following sub-sections.

3.2.1 Annual distribution of studies

The research protocol restricted the time frame for data collection to publications between 2020 and 2026 to ensure t relevance. Although the highest number of studies was published in 2022 and 2024, an overall upward trend in publications on the topic can be observed. This growth may be attributed to the rapid expansion of e-commerce within the FMCG sector following the COVID-19 pandemic, which accelerated the shift from traditional retail towards online fulfilment models. In addition, the increasing integration of artificial intelligence and machine learning tools into warehouse and distribution centre operations has driven further academic interest in proactive slotting and SKU allocation optimisation. Figure 2 presents the detailed annual distribution of the included studies.

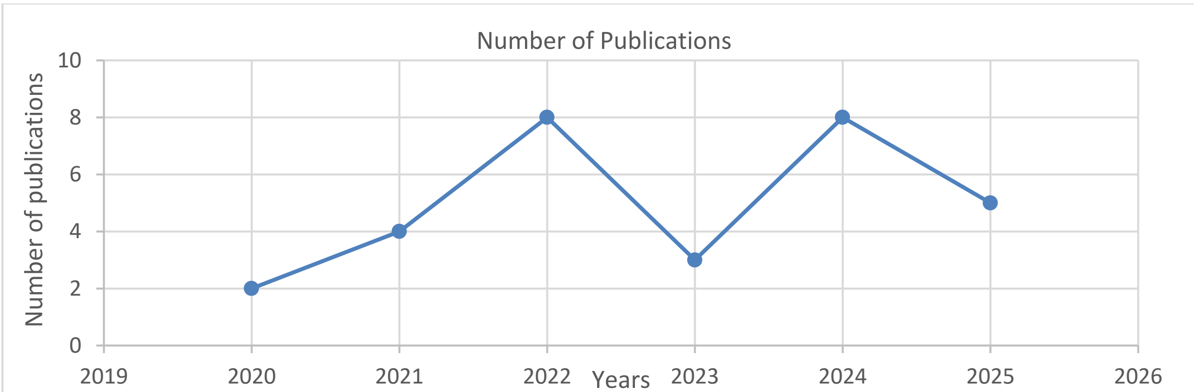

Figure 2. Line graph of the number of publications per year

3.2.2 Countries of study

With contributions from Asia, Europe, the Middle East, Africa, and the Americas, the included studies' geographic distribution demonstrates the interest in slotting, SKU allocation, and warehouse optimisation on a global scale. A sizable amount of the research came from Asian nations like China, Japan, South Korea, Malaysia, Indonesia, Vietnam, and India, indicating a high level of academic and business interest in intelligent warehousing systems and e-commerce fulfillment. While North and South American research was represented by the United States, Canada, Peru, and Colombia, European contributions were noted from the United Kingdom, Italy, Russia, Estonia, Finland, Norway, Latvia, and France. Further research was carried out in Thailand, Singapore, Hong Kong, Taiwan, the United Arab Emirates, and Morocco, demonstrating a varied environment for international cooperation. Overall, this broad geographic distribution shows that research on slotting tactics, AI-enabled optimisation, and picking productivity enhancements is pertinent worldwide, especially in digitally changing distribution center settings.

3.2.3 Impact of Slotting on Picking Productivity

The implementation of slotting strategies has an impact on distribution centre operations by aligning physical storage layouts with operational requirements. Strategic SKU placement reduces picker travel distances and retrieval times, addressing one of the largest contributors to DC labour effort while improving material flow and alleviating order fulfilment bottlenecks (Ou et al., 2024; Thi Quynh and Lao, 2024; Kalkha et al., 2024; Zennaro et al., 2022; Alherimi et al., 2024; Yusuf-Madhani et al., 2024). By organising inventory according to demand characteristics and movement frequency, demand-oriented slotting approaches enhance responsiveness and picking productivity. Classification techniques such as ABC and FSN analysis enable high-turnover items to be positioned within forward-picking zones or near inbound and outbound points, reducing handling effort and supporting faster order fulfilment (Ochoa-González et al., 2025; Leung et al., 2022; Thi Quynh and Lao, 2024; Zhai et al., 2025). These strategies also contribute to improved space utilisation by balancing product dimensions, storage density, and accessibility, thereby minimising unused capacity without compromising operational efficiency (Ahmed et al., 2023).

Research also further emphasises the role of correlation-based storage strategies, where frequently co-ordered items are located in close proximity to streamline picking routes. Techniques such as frequent itemset grouping reduce the number of shelf or pod visits required per order, improving route efficiency and overall workflow performance (Ma et al., 2023; Kim et al., 2020; Lang et al., 2020; Zhai et al., 2025). Beyond productivity gains, well-designed slotting layouts can improve ergonomics and workforce conditions by reducing unnecessary physical strain and promoting more stable and standardised workflows (Ahmed et al., 2023; Hipolito-Osorio et al., 2025; Shah, 2023). Finally, recent research highlights a clear transition toward technology-driven slotting approaches, where artificial intelligence and machine learning enable predictive and proactive storage allocation. These intelligent systems analyse demand variability, seasonal trends, and order patterns to support dynamic layout adjustments, allowing distribution centres to maintain high service levels while operating more efficiently and responsively (Kang et al., 2024; Kalkha et al., 2024; Hipolito-Osorio et al., 2025; Shah, 2023).

3.2.4 Quantifiable metrics to measure DC productivity

The impact of slotting strategies on distribution centre productivity is commonly quantified using a combination of t spatial and operational performance metrics derived from analytical modelling and simulation-based studies. Researchers frequently evaluate indicators such as average picker or robot travel distance per order, picking cycle time, and the number of storage unit movements (e.g., pod or rack visits) required to complete a group of orders (Ma et al., 2023; Lee et al., 2022; Kigure et al., 2025; Kim et al., 2020). More advanced performance assessments incorporate throughput (TP), defined as the ratio of fulfilled orders to total demand over a planning horizon, and order fill rate (OFR), which measures the proportion of orders delivered completely and on time (Yuan et al., 2021; Hipolito-Osorio et al., 2025; Shah, 2023). To validate these metrics under realistic operating conditions, many studies employ discrete-event simulation environments, such as Arena, enabling researchers to capture the stochastic nature of order arrivals, labour availability, and resource constraints (Martínez et al., 2021; Ochoa-González et al., 2025; Hipolito-Osorio et al., 2025).

Slotting interventions demonstrate substantial, quantifiable improvements across a range of warehouse configurations. Effective storage assignment has been shown to reduce average picker travel distance by approximately 29% to 60%, depending on facility layout and routing policies (Ahmed et al., 2023; Quynh and Lao, 2024). Similarly, total picking time reductions between 10% and 25.75% have been reported, with specialised kitting environments achieving even greater savings of up to 36%–49% (Alherimi et al., 2024; Yusuf-Madhani et al., 2024; Ahmed et al., 2023). Correlation-based slotting algorithms further enhance performance, improving overall picking efficiency by 6.31% to 23.8% (Ma et al., 2023; Wu and Chen, 2022). In technologically advanced environments, transitions from random storage to intelligent slotting strategies, such as time-series clustering, have generated efficiency gains of up to 61%–69% under specific routing scenarios (Kalkha et al., 2024). Additionally, integrating machine learning with strategic slotting has demonstrated improvements in inventory turnover of up to 33.43% and reductions in average inventory levels by approximately 30% (Ochoa-González et al., 2025).

Turnover rate and item popularity remain critical drivers of slotting performance. ABC classification is widely used to position high-frequency "Class A" items near shipping or depot locations, thereby reducing travel requirements for the majority of picking activities (Serna-Ampuero et al., 2022; Yusuf-Madhani et al., 2024; Quynh and Lao, 2024). Item correlation, often identified through market basket analysis, is another key determinant; storing frequently co-ordered items in proximity reduces the number of required rack or pod visits and shortens picking routes (Lang et al., 2020; Ahmed et al., 2023; Kim et al., 2020). Some studies extend this concept by incorporating quantity correlation, which considers the relative volumes of SKUs within orders to minimise further rack movements (Zhai et al., 2025). Moreover, demand volatility in e-commerce environments necessitates responsive slotting strategies capable of adapting to rapidly shifting SKU popularity and seasonal fluctuations (Lam et al., 2023; Wu and Chen, 2022).

Physical slot characteristics also play a significant role in productivity outcomes. Proximity to inbound and outbound points is frequently identified as the most influential spatial factor affecting picking efficiency (Quynh and Lao, 2024). In multi-tier racking systems, vertical positioning introduces additional retrieval time penalties, making ground-level pick-face zones particularly valuable for high-frequency items (Lam et al., 2023; Quynh and Lao, 2024). Furthermore, slot desirability is dynamic rather than static; optimal placement depends not only on distance to the depot but also on the spatial relationship to previously assigned, highly correlated SKUs (Kim et al., 2020). Finally, the balance between forward and reserve storage areas influences overall workflow stability, as maintaining an appropriate lean buffer in forward zones must be weighed against the replenishment effort required from reserve locations (Shah, 2023; Leung et al., 2022).

3.2.5 How AI can enable proactive slotting

Machine learning and optimisation algorithms play a central role in enabling AI-driven predictive slotting by transforming historical order data and real-time operational metrics into proactive storage decisions that anticipate future demand patterns (Wu and Chen, 2022; Lam et al., 2023; Kang et al., 2024).

Predictive slotting begins with advanced forecasting models that analyse historical demand to identify SKU turnover trends, affinity relationships, and evolving order profiles (Wu and Chen, 2022; Ochoa-González et al., 2025). Nonlinear Autoregressive (NAR) neural networks have demonstrated forecasting accuracies of up to 98.79%, providing a reliable basis for dynamic storage allocation decisions (Wu and Chen, 2022). Similarly, Adaptive Network-based Fuzzy Inference Systems (ANFIS) are applied to estimate SKU quantities in upcoming e-commerce orders, enabling warehouses to adjust pick-face inventory levels before demand materialises (Lam et al., 2023). In more complex environments characterised by high SKU diversity, ensemble learning approaches incorporating multi-layer stacking and k-fold bagging have been used to predict order similarity, supporting proactive batching and reservation strategies (Kang et al., 2024).

Following demand prediction, optimisation algorithms determine the optimal allocation of SKUs to storage locations while balancing multiple objectives and operational constraints (Yuan et al., 2021; Zhai et al., 2025). Multiobjective genetic algorithms, particularly improved NSGA-III variants integrated with good point set theory, aim to maximise picking efficiency while minimising resource loss (Wu and Chen, 2022). Adaptive Large Neighbourhood Search (ALNS) has proven effective for large-scale robotic fulfilment systems by maximising correlation between replenishment items and existing inventory, with parallelised variants (pALNS) addressing stochastic demand through Sample Average Approximation subproblems (Li et al., 2024; Zhai et al., 2025). In cases where objective functions cannot be analytically defined, black-box optimisation techniques such as simulated annealing explore solution spaces using machine-learned surrogate models (Kigure et al., 2025). Additionally, Variable Neighbourhood Search (VNS) approaches have demonstrated strong performance in solving commodity storage assignment problems by maximising overall correlation across storage zones (Ma et al., 2023).

A key advancement highlighted in the literature is the shift from static slotting towards dynamic and proactive reslotting frameworks (Leung et al., 2022; Kang et al., 2024). Digital twin-based systems virtualise warehouse operations, enabling prescriptive analytics that synchronise order fulfilment and replenishment processes using near-real-time data (Leung et al., 2022). Predictive order reservation mechanisms further enhance consolidation efficiency by deferring orders that exhibit high similarity with anticipated future demand, thereby improving batching performance (Kang et al., 2024). Proactive lookahead strategies also replenish forward pick-face areas based on forecasted demand, reducing repeated travel to reserve storage locations and improving overall operational fluidity (Lam et al., 2023; Leung et al., 2022).

Effective AI-driven slotting must incorporate physical and operational constraints to ensure practical feasibility (Shah, 2023; Zhai et al., 2025). Recent approaches account for category-quantity correlations, ensuring that storage allocation reflects not only SKU popularity but also the quantity ratios present in customer orders (Zhai et al., 2025). Additional considerations include bin capacity limitations, workload balancing across aisles to prevent congestion, and time-window constraints associated with same-day delivery requirements (Yuan et al., 2021; Ohmori and Maki, 2025; Zhai et al., 2025). Studies also identify strategic capacity buffers—such as reserving a portion of rack space—to maintain flexibility for dynamic adjustments. Furthermore, text-granulation clustering techniques support decision interpretability by grouping SKUs semantically, enabling AI-driven slotting recommendations to remain transparent and actionable for warehouse managers (Lang et al., 2020).

3.2.7 Key Summary of findings

The table below (Table 2), presents a clear summary of the findings of the data extracted from the review and clearly states what productivity gains are made and what corresponding AI measures were taken.

Table 2. Summary of findings of studies included for review

Source	Finding of Productivity Gains	How AI Enhanced Proactive Slotting
Ahmed et al. 2023	36% to 49% reduction in kitting times and 30% to 36% improvement in space utilisation	Utilises the Apriori Algorithm for Market Basket Analysis to position frequently co-occurring parts closer to the picker
Al Mashalah et al. 2022	Proactive strategies decrease the impact of cost disruptions and enhance firm performance	Highlights leveraging Data Mining and Social Media Analytics to anticipate consumer demand uncertainty and enhance sustainability

Alherimi et al. 2024	10% reduction in picking time and 14.8% increase in space utilisation	Integrates Digital Twins and AI to enable proactive problem-solving and improved resource allocation through simulation
Hipolito-Osorio et al. 2025	50% reduction in order operation time and 24% decrease in picking errors	Uses Generative AI (GenAI) to standardise order management and validate data, eliminating incomplete order errors
Kalkha et al. 2024	61% to 69% efficiency gains under S-shape and midpoint routing	Uses Time Series Clustering (SOM, K-Means, AHC) to group items with similar demand patterns during the "put away" phase
Kang et al. 2024	Up to 6.1% improvement in order turnover time	Employs Ensemble Learning to predict order similarities, enabling a Predictive Order Reservation mechanism to defer batching for higher efficiency
Kigure et al. 2025	Higher probability (33.3%) of finding optimal slotting solutions compared to standard annealing	Employs Quantum Annealing (QA) combined with a machine-learned surrogate model to search for optimal assignments in a black-box environment
Kim et al. 2020	22.6% lower average travel distance than conventional heuristic methods	Employs Association Analysis and frequent itemset grouping to assign correlated SKUs to slots in proximity
Lam et al. 2023	63.28% reduction in the order picking process time	Combines ANFIS for demand prediction with Adaptive Genetic Algorithms to generate optimal stock replenishment plans for pick faces
Lang et al. 2020	40.5% to 57.9% improvement in average order picking distance	Utilises Text-Granulation Clustering based on semantic learning to group products by attributes like name and colour for interpretable allocation
Lee et al. 2022	21.56% to 22.69% shorter average travel distance per SKU	Not applicable (Uses mixed-integer programming and heuristics)
Leung et al. 2022	80.9% reduction in total daily traveling distance	Integrates Digital Twins and Neuro-Fuzzy machine learning for Total Inbound Synchronisation and proactive lookahead fulfillment
Li et al. 2024	At least 10% improvement in objective value over other heuristics	Employs Adaptive Large Neighborhood Search (ALNS) to maximise the correlation degree between replenishment and already-stored items
Ma et al. 2023	Order picking efficiency improved by more than 6.31%	Employs Variable Neighborhood Search (VNS) with self-adaption and simulated annealing to match SKU storage patterns with dynamic demand
Martínez et al. 2021	20.9% reduction in time out of warehouse and 30% reduction in economic losses	Not applicable (Uses traditional Lean tools like Kanban and FEFO)
Ochoa-González et al. 2025	33.43% improvement in inventory turnover and 60% decrease in picking time	Uses Machine Learning-based demand forecasting (ARIMA) to optimise stock turnover and predict future demand patterns
Ohmori and Maki 2025	Substantial picking and replenishment cost savings compared to rule-based heuristics	Not applicable (Uses Mixed-Integer Non-Linear Programming and Lagrange relaxation)

Ou et al. 2024	Up to 60% reduction in picking time when optimised with physical layout changes	Uses Hybrid Genetic Algorithms and K-Means clustering to optimise storage assignments and balance picker workloads
Quynh and Lao 2024	29% reduction in total travel distance compared to the current layout	Not applicable (Uses traditional ABC Analysis and Class-Based Storage)
Serna-Ampuero et al. 2022	37.77% reduction in picking search time and 47.99% reduction in fictitious stock	Not applicable (Uses Lean Warehousing: 5S, ABC classification, and Q,r review)
Shah 2023	Maximises customer service levels and Throughput (0.9994)	Not applicable (Uses mathematical modelling for Lean buffer design)
Voronova 2022	Automated shelving systems collecting orders 10 times faster than humans	Employs Smart Slotting driven by 3D-modeling and Digital Twins to simulate employee movements and equipment mileage
Wu and Chen 2022	Improved goods selection efficiency by 23.8%	Combines NAR neural networks for demand prediction with NSGA-III algorithms for multiobjective space allocation optimisation
Yuan et al. 2021	32.7% to 36.6% reduction in pod visits compared to random assignment	Uses improved Simulated Annealing to minimise robot travel distance while balancing corridor workload to prevent congestion
Yusuf-Madhani et al. 2024	25.75% average reduction in picking time	Uses hybridisation of Ant Colony Optimisation and Tabu Search (ACO-TS) for routing based on ZABLS slotting results
Zennaro et al. 2022	Optimised picking covers 51% of warehouse costs	Mentions AI and data mining for capturing buying behavior, though focuses on the broader logistics framework
Zhai et al. 2025	2.84% to 38.94% reduction in rack movements	Uses Parallel Adaptive Large Neighborhood Search (pALNS) to account for stochastic order uncertainty and quantity correlations

3.2.8 Further Exploration of AI Techniques

1. NAR Neural Networks:
Nonlinear Autoregressive (NAR) neural networks analyse historical order data to forecast SKU demand with an accuracy of up to 98.79%. Their outputs provide a reliable basis for proactive storage allocation, replacing reactive replenishment decisions with anticipatory positioning of inventory before demand peaks (Wu & Chen, 2022).

2. ANFIS (Adaptive Neuro-Fuzzy Inference Systems):
ANFIS combines the learning capacity of neural networks with the interpretability of fuzzy logic to estimate incoming e-commerce order quantities. Paired with Adaptive Genetic Algorithms, it generates optimised replenishment schedules so that pick-face inventory is refreshed before demand materialises, avoiding costly mid-shift stockouts (Lam et al., 2023).

3. Ensemble Learning & Predictive Order Reservation:
Multi-layer stacking and k-fold bagging techniques predict order similarity across high-SKU diversity environments. Orders identified as highly similar to anticipated future demand are deferred rather than immediately batched, enabling more efficient consolidation and reducing unnecessary early picks across storage zones (Kang et al., 2024).

4. NSGA-III Multiobjective Genetic Algorithms:
An improved NSGA-III variant, integrated with good point set theory, simultaneously maximises picking efficiency while minimising resource loss. The algorithm produces a Pareto-optimal front of slotting configurations, giving warehouse managers a set of balanced solutions that reflect real-world trade-offs between competing operational objectives (Wu & Chen, 2022).

5. Adaptive Large Neighbourhood Search (ALNS / pALNS):
ALNS maximises the correlation between incoming replenishment items and inventory already stored in robotic fulfilment systems. Its parallelised variant, pALNS, addresses stochastic demand uncertainty through Sample Average Approximation subproblems, accounting for both quantity correlations and variable order profiles to improve slotting robustness at scale (Li et al., 2024; Zhai et al., 2025).

6. Quantum Annealing & Machine-Learned Surrogate Models:
Where objective functions cannot be analytically defined, Quantum Annealing explores vast slotting solution spaces guided by a machine-learned surrogate model. This black-box optimisation approach achieves a higher probability of finding optimal assignments compared to standard simulated annealing, making it particularly suited to highly variable or non-standard warehouse configurations (Kigure et al., 2025).

7. Variable Neighbourhood Search (VNS):
Self-adaptive VNS combined with simulated annealing matches SKU storage patterns to evolving demand by maximising correlation across storage zones. The algorithm alternates between neighbourhood structures to escape local optima, producing consistent efficiency improvements in commodity storage assignment problems where demand shifts continuously (Ma et al., 2023).

8. Digital Twins & Neuro-Fuzzy Machine Learning:
Digital twin environments virtualise warehouse operations using near-real-time data, enabling prescriptive analytics that synchronise replenishment with fulfilment demand. Integrated neuro-fuzzy machine learning supports proactive lookahead fulfilment, while 3D simulation models employee movements and equipment mileage to identify slotting inefficiencies before they occur physically (Leung et al., 2022; Voronova, 2022; Alherimi et al., 2024).

9. Time Series Clustering; SOM, K-Means, AHC:
Self-Organising Maps, K-Means, and Agglomerative Hierarchical Clustering group SKUs by shared demand patterns during the put-away phase. Items with aligned demand profiles are co-located in adjacent storage positions, substantially shortening picker travel under both S-shape and midpoint routing strategies without requiring changes to the physical warehouse layout (Kalkha et al., 2024).

10. Association Analysis & Apriori Algorithm:
Market basket analysis using the Apriori algorithm identifies frequent co-purchase itemsets and co-occurring component parts. SKUs with strong affinity relationships are assigned to adjacent slots, reducing multi-zone picks per order and shortening travel paths. In kitting environments, this approach has also delivered meaningful improvements in space utilisation alongside travel distance reductions (Ahmed et al., 2023; Kim et al., 2020).

11. Text-Granulation Semantic Clustering:
Products are grouped according to semantic attributes — such as name, colour, and product category — using text-granulation clustering built on natural language similarity scoring. A key advantage of this technique is its interpretability; slotting recommendations remains transparent and understandable to warehouse managers, supporting practical adoption and informed decision-making (Lang et al., 2020).

12. Hybrid Genetic Algorithms & K-Means Clustering:
K-Means clustering first segments SKUs into demand-aligned groups, after which a Hybrid Genetic Algorithm optimises their physical storage assignment across available locations. The combined approach additionally incorporates workload balancing across picker aisles, preventing congestion hotspots from forming in high-density areas of the fulfilment centre during peak periods (Ou et al., 2024).

13. ARIMA & ML-Based Demand Forecasting:
ARIMA-based machine learning models forecast future demand patterns to guide proactive stock positioning. By anticipating which SKUs will be needed ahead of order arrival, warehouses can pre-position inventory to minimise travel distances and reduce pick-face stockouts, with improvements reported in both inventory turnover rates and overall picking speed (Ochoa-González et al., 2025).

14. Ant Colony Optimisation + Tabu Search (ACO-TS):
A hybridisation of Ant Colony Optimisation and Tabu Search drives routing decisions on top of pre-determined slotting assignments. Pheromone-based path reinforcement continuously refines picker routes while Tabu lists prevent revisiting recently explored solutions, allowing the algorithm to escape local optima and identify consistently efficient pick paths across varied order profiles (Yusuf-Madhani et al., 2024).

15. Generative AI (GenAI) for Order Validation:
Generative AI standardises and validates incoming order data before it enters the fulfilment pipeline, eliminating incomplete or malformed entries at the source. By cleaning demand signals upstream, downstream slotting and picking operations benefit from more accurate order profiles, fewer error-driven interruptions, and a measurable reduction in fulfilment mistakes at the pick face (Hipolito-Osorio et al., 2025).

16. Improved Simulated Annealing:
An enhanced simulated annealing algorithm minimises robot travel distance in Goods-to-Person fulfilment systems while simultaneously balancing workload across corridor zones to prevent congestion. Stochastic perturbations enable the algorithm to escape sub-optimal storage assignments over iterative cycles, producing pod visit reductions of up to 36.6% compared to random assignment baselines (Yuan et al., 2021).

5. Conclusion

This systematic literature review achieved its objectives by evaluating how slotting strategies influence distribution centre picking productivity and by scoping how artificial intelligence enables a shift from reactive to proactive slotting optimisation. The synthesis of 27 studies confirms that strategic SKU placement can significantly reduce travel distance, improve throughput, and enhance operational performance, while measurable KPIs such as picking time, travel distance, and order fulfilment metrics provide a structured basis for quantifying these impacts.

A key contribution of this research lies in integrating productivity-enhancing slotting techniques with emerging AI-driven predictive approaches, demonstrating a clear transition toward proactive and data-driven decision-making frameworks. By evaluating prior research and linking quantifiable metrics with AI-enabled analytics, this SLR establishes a structured theoretical foundation that can inform future practical implementation in distribution centre environments. Overall, the findings confirm that all research objectives were met while highlighting the growing role of predictive analytics, optimisation algorithms, and digital twin technologies in shaping next-generation slotting strategies.

Despite these contributions, several limitations should be acknowledged. The review was restricted to studies published between 2020 and 2026 and focused primarily on FMCG-oriented distribution environments, which may limit generalisability to other industries or legacy warehouse systems. Furthermore, many included studies relied on simulation or modelling approaches rather than real-world experimental validation, creating a gap between theoretical performance improvements and operational feasibility.

Future research should therefore prioritise empirical case studies and quasi-experimental implementations within live distribution centres to validate AI-driven slotting under real constraints such as labour variability, reslotting costs, and system integration challenges. Expanding this work could involve developing decision-support frameworks that balance productivity gains with operational disruption, exploring human-centric and interpretable AI approaches, and investigating scalable dynamic slotting strategies that integrate forecasting, optimisation, and warehouse execution systems in real time.

References

Ahmed, S., Parvathaneni, D. and Shareef, I., Reorganization of inventory to improve kitting efficiency and maximize space utilization, Manufacturing Letters, vol. 35, pp. 1366–1377, 2023.

Albliwi, S., Anthony, J., Lim, S.A.H. and van der Wiele, T., Critical failure factors of Lean Six Sigma: A systematic literature review, International Journal of Quality & Reliability Management, vol. 31, no. 9, pp. 1012-1030, 2014.

Alherimi, N., Saihi, A. and Ben-Daya, M., A systematic review of optimization approaches employed in digital warehousing transformation, IEEE Access, vol. 12, pp. 138139–138164, 2024.

Al Mashalah, H., Hassini, E., Gunasekaran, A. and Bhatt (Mishra), D., The impact of digital transformation on supply chains through e-commerce: Literature review and a conceptual framework, Transportation Research Part E, vol. 165, p. 102837, 2022.

De Koster, R., Le-Duc, T. and Roodbergen, K. J., Design and control of warehouse order picking: A literature review, European Journal of Operational Research, vol. 182, no. xx, 2007.

Gu, J., Goetschalckx, M. and McGinnis, L. F., Research on warehouse design and performance evaluation: A comprehensive review, European Journal of Operational Research, vol. 203, no. xx, 2010.

Hipolito-Osorio, M., Siles-Olivera, A., Mendez-Pallares, B. and Velásquez-Costa, J., Integrated model for order fulfillment: Standard work with GenAI, SLP, WMS, and augmented reality in distribution operations, Proceedings of the 11th World Congress on Mechanical, Chemical, and Material Engineering (MCM'25), Paris, France, August 2025, Paper No. ICMIE 186.

Kalkha, H., Khiat, A., Bahnasse, A. and Ouajji, H., Enhancing warehouse efficiency with time series clustering: A hybrid storage location assignment strategy, IEEE Access, vol. 12, pp. 51839–51857, 2024.

Kang, Y., Qu, Z. and Yang, P., Enhancing e-commerce warehouse order fulfillment through predictive order reservation using machine learning, IEEE Transactions on Automation Science and Engineering, 2024

Kigure, H., Baba, T., Taniguchi, M. and Kaji, H., Black-box optimization of the storage location assignment problem in logistics centers using an annealing algorithm, IEEE Transactions on Quantum Engineering, vol. 7, pp. 1–15, 2026.

Kim, J., Méndez, F. and Jimenez, J., Storage location assignment heuristics based on slot selection and frequent itemset grouping for large distribution centers, IEEE Access, vol. 8, pp. 187863–187872, 2020.

Lam, H. Y., Ho, G. T. S., Mo, D. Y. and Tang, V., Responsive pick face replenishment strategy for stock allocation to fulfil e-commerce order, International Journal of Production Economics, vol. 264, p. 108976, 2023.

Lang, Q., Pan, X. and Liu, X., A text-granulation clustering approach with semantics for e-commerce intelligent storage allocation, IEEE Access, vol. 8, pp. 161863–161872, 2020.

Lee, T., Lee, J. and Hong, S., Batch assorting for worker-following assortment carts in parallel-aisle order-assorting systems, IEEE Access, vol. 10, pp. 43336–43349, 2022.

Leung, E. K. H., Lee, C. K. H. and Ouyang, Z., From traditional warehouses to Physical Internet hubs: A digital twin-based inbound synchronization framework for PI-order management, International Journal of Production Economics, vol. 244, p. 108353, 2022.

Li, R., Deng, X. and Ma, Y., Item storage assignment problem in robotic mobile fulfillment systems with nonempty pods, IEEE Access, vol. 12, pp. 51046–51061, 2024.

Ma, Z., Wu, G., Ji, B., Wang, L., Luo, Q. and Chen, X., A novel scattered storage policy considering commodity classification and correlation in robotic mobile fulfillment systems, IEEE Transactions on Automation Science and Engineering, vol. 20, no. 2, pp. 1020–1033, 2023.

Namay-Zevallos, W., Martinez, M., Soto, C. and Salas, R., A combined demand management and lean tools model at a Peruvian meat products company, Proceedings of the 7th International Conference on Industrial and Business Engineering (ICIBE 2021), Macau, China, September 27–29, 2021, pp. 219–225.

Ochoa-González, A., Mendoza-Quintanilla, K. and Quiroz-Flores, J. C., An integrated lean and machine learning approach to inventory management in automotive accessories SMES, International Journal of Engineering Trends and Technology, vol. 73, no. 9, pp. 288–308, 2025.

Ohmori, S. and Maki, K. M., Robot-manual forward-reserve allocation problem, IEEE Access, vol. 13, pp. 121540–121556, 2025.

Ou, S., Ismail, Z. H. and Sariff, N., Hybrid genetic algorithms for order assignment and batching in picking system: A systematic literature review, IEEE Access, vol. 12, pp. 14389–14406, 2024.

Serna-Ampuero, M. A., Arias-Navarro, M. and Quiroz-Flores, J. C., Inventory management model under the lean warehousing approach to reduce the rate of returns in SME distributors, Proceedings of the 8th International Conference on Industrial and Business Engineering (ICIBE 2022), Macau, China, September 27–29, 2022, pp. 417–422.

Shah, B., What should be lean buffer threshold for the forward-reserve warehouse?, International Journal of Productivity and Performance Management, vol. 72, no. 2, pp. 361–387, 2023.

Thi Quynh, N. L. and Lao, K. K., Storage assignment strategy to reduce travel distance: Case study in FMCG distribution center, Proceedings of the IEOM International Conference, Ho Chi Minh City, Vietnam, 2024.
Voronova, O., Improvement of warehouse logistics based on the introduction of lean manufacturing principles, Transportation Research Procedia, vol. 63, pp. 919–928, 2022.
Wu, P. and Chen, Y., Establishing a novel algorithm for highly responsive storage space allocation based on NAR and improved NSGA-III, Complexity, vol. 2022, pp. 1–12, 2022.
Yuan, R., Li, J., Wang, W., Dou, J. and Pan, L., Storage assignment optimization in robotic mobile fulfillment systems, Complexity, vol. 2021, pp. 1–11, 2021.
Yusuf-Madhani, G., Kumala-Sriwana, I. and Nashir-Ardiansyah, M., Sequential model of FSN classification with Zabls slotting and vehicle routing problem using hybridization of ant colony optimization and tabu search to reduce picking time, Journal of Industrial Engineering and Management, vol. 17, no. 3, pp. 853–872, 2024.
Zennaro, I., Finco, S., Calzavara, M. and Persona, A., Implementing e-commerce from logistic perspective: Literature review and methodological framework, Sustainability, vol. 14, no. 2, p. 911, 2022.
Zhai, M., Wang, Z., Sheu, J. B. and Hu, B., Item storage assignment for mobile-rack warehouses in the Industry 4.0 era, IEEE Transactions on Engineering Management, vol. 72, pp. 1–13, 2025

Biographies

Malcolm Smith is a Master's student in Industrial Engineering at Stellenbosch University, specialising in logistics and supply chain systems, and holds a Bachelor's degree in Industrial Engineering from the same institution. His academic interests centre on logistics resource engineering and shop floor planning, with a particular focus on applying the Theory of Constraints to identify critical bottlenecks and optimise system performance through detailed, data-driven analysis. He is especially interested in how targeted attention to constraints can unlock significant productivity and efficiency gains across complex operational environments.

Beyond his academic pursuits, Malcolm has a strong passion for outdoor activities, most notably fly fishing, which has taken him on extensive travel experiences to remote and diverse locations. His active lifestyle also includes swimming, running, surfing, and canoeing, reflecting a balance between analytical rigour and physical challenge.

Mia Mangaroo-Pillay is a Senior Lecturer in the Department of Industrial Engineering at Stellenbosch University, South Africa, where she is actively involved in teaching, research, and postgraduate supervision. She holds a PhD in Engineering, and her academic work centres on operational excellence, human factors engineering, lean philosophy, and Industry 4.0/5.0. Her research explores the integration of advanced technologies and human-centred approaches to enhance organisational performance and sustainable industrial systems.

Vanya Jansen is an Adjunct Senior Lecturer in the Department of Industrial Engineering at Stellenbosch University, South Africa, where she contributes to teaching and industry-aligned education within logistics, supply chain management, and industrial engineering. Her work focuses on operations management, logistics systems, and supply chain optimisation, with particular emphasis on integrating strategic, tactical, and operational perspectives in warehousing and transportation environments. She is actively involved in postgraduate programmes, including the Logistics Resource Engineering module, where she promotes practical, industry-focused learning and systems thinking. Jansen's academic and professional interests include supply chain strategy, optimisation, inventory and production management, and simulation-based decision support, reflecting a strong commitment to bridging theory and real-world industrial application.

Appendix A

Table 3. list of sources includes for review

Title	Author(s)	Publication Date
A Novel Scattered Storage Policy Considering Commodity Classification and Correlation in Robotic Mobile Fulfillment Systems	Zhongqiang Ma, Guohua Wu, Bin Ji, Qizhang Luo, Ling Wang, and Xinjiang Chen	06-Jun-22
A Systematic Review of Optimization Approaches Employed in Digital Warehousing Transformation	Nadin Alherimi, Afef Saihi, and Mohamed Ben-Daya	18-Sept-24
A Text-Granulation Clustering Approach With Semantics for E-Commerce Intelligent Storage Allocation	Qi Lang, Xuejun Pan, and Xiaodong Liu	03-Sept-20
A Combined Demand Management and Lean Tools Model at a Peruvian Meat Products Company	Michel Martínez, Christian Soto, Rosa Salas, and Wilder Namay-Zevallos	27-Sept-21
An Integrated Lean and Machine Learning Approach to Inventory Management in Automotive Accessories SMES	Adolfo Ochoa-González, Kevin Mendoza-Quintanilla, and Juan Carlos Quiroz-Flores	30-Sept-25
Batch Assorting for Worker-Following Assortment Carts in Parallel-Aisle Order-Assorting Systems	Taehoon Lee, Jeongman Lee, and Soondo Hong	21-Apr-22
Black-Box Optimization of the Storage Location Assignment Problem in Logistics Centers Using an Annealing Algorithm	Hiromitsu Kigure, Takeshi Baba, Makoto Taniguchi, and Hirotaka Kaji	19-Dec-25
Storage Assignment Optimization in Robotic Mobile Fulfillment Systems	Ruiping Yuan, Juntao Li, Wei Wang, Jiangtao Dou, and Luke Pan	25-Nov-21
Establishing a Novel Algorithm for Highly Responsive Storage Space Allocation Based on NAR and Improved NSGA-III	Peijian Wu and Yulu Chen	24-Feb-22
Enhancing E-Commerce Warehouse Order Fulfillment Through Predictive Order Reservation Using Machine Learning	Yuexin Kang, et al.	22-Jul-24
Enhancing Warehouse Efficiency With Time Series Clustering: A Hybrid Storage Location Assignment Strategy	Hicham Kalkha, Azeddine Khiat, Ayoub Bahnasse, and Hassan Ouajji	10-Apr-24
From traditional warehouses to Physical Internet hubs: A digital twin-based inbound synchronization framework for PI-order management	Eric K.H. Leung, Carmen Kar Hang Lee, and Zhiyuan Ouyang	10-Nov-21
Hybrid Genetic Algorithms for Order Assignment and Batching in Picking System: A Systematic Literature Review	Samnang Ou, Zool Hilmi Ismail, and Nohaidda Sariff	23-Jan-24
Inventory Management Model under the Lean Warehousing Approach to Reduce the Rate of Returns in SME Distributors	Maria Antonieta Serna-Ampuero, Mauricio Arias-Navarro, and Juan Carlos Quiroz-Flores	27-Sept-22
Implementing E-Commerce from Logistic Perspective: Literature Review and Methodological Framework	Ilenia Zennaro, Serena Finco, Martina Calzavara, and Alessandro Persona	14-Jan-22
Improvement of warehouse logistics based on the introduction of lean manufacturing principles	Olga Voronova, et al.	2022
Integrated Model for Order Fulfillment: Standard Work with GenAI, SLP, WMS, and Augmented Reality in Distribution Operations	Mylena Hipolito-Osorio, Allison Siles-Olivera, Baldomero Mendez-Pallares, and José Velásquez-Costa	Aug-25

Item Storage Assignment Problem in Robotic Mobile Fulfillment Systems With Nonempty Pods	Rubo Li, Xudong Deng, and Yunfeng Ma	08-Apr-24
Item Storage Assignment for Mobile-Rack Warehouses in the Industry 4.0 Era	Mengyue Zhai, Zheng Wang, Bo Hu, and Jiuh-Biing Sheu	17-Apr-25
Reorganization of inventory to improve kitting efficiency and maximize space utilization	Syed Ahmed, Dileep Parvathaneni, and Iqbal Shareef	2023
Responsive pick face replenishment strategy for stock allocation to fulfil e-commerce order	H.Y. Lam, G.T.S. Ho, Daniel Y. Mo, and Valerie Tang	20-Jul-23
Robot-Manual Forward-Reserve Allocation Problem	Shunichi Ohmori, et al.	Apr-25
Sequential Model of FSN Classification with Zabls Slotting and Vehicle Routing Problem Using Hybridization of Ant Colony Optimization and Tabu Search to Reduce Picking Time	Genta Yusuf-Madhani, Iphov Kumala-Sriwana, and Muhammad Nashir-Ardiansyah	Oct-24
Storage Location Assignment Heuristics Based on Slot Selection and Frequent Itemset Grouping for Large Distribution Centers	Junwoo Kim, Francis Méndez, and Jesus Jimenez	16-Oct-20
Storage Assignment Strategy To Reduce Travel Distance: Case Study In FMCG Distribution Center	Nhi Le Thi Quynh and Khai Kien Lao	2024
The impact of digital transformation on supply chains through e-commerce: Literature review and a conceptual framework	Heider Al Mashalah, Elkafi Hassini, Angappa Gunasekaran, and Deepa Bhatt (Mishra)	02-Aug-22
What should be lean buffer threshold for the forward-reserve warehouse?	Bhavin Shah	2023