

MANAGERIAL DESIGN OF SLOTTING AND PICKING IN SMART WAREHOUSES

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Abstract: The article develops a managerial framework for the joint design of storage location assignment (slotting) and order picking in smart warehouses. Design decisions are arranged in strategic, tactical and operational layers, coupled with digital enablers and human-centric constraints, and closed into a decision cycle with a re-slotting trigger. A stylised computational case compares six configurations, from manual random storage to a goods-to-person system, by an order cycle time model, cost per order line and a weighted utility under two managerial priority profiles. Supportive technologies combined with affinity-based slotting give the lowest cost per line, whereas hybrid and substitutive automation win on throughput and ergonomic load and reach cost parity only at about five times the base volume. The preferred configuration therefore follows from managerial priorities and volume rather than from technology alone.

Keywords: smart warehouse, order picking, storage location assignment, slotting, managerial design, Order Picking 4.0, human-centric logistics, digital twin, warehouse performance.

1. Introduction

Warehouses have moved from the periphery of supply chains to their centre. E-commerce, same-day delivery, omnichannel retailing and repeated supply chain disruptions have turned them into technology-enriched fulfilment factories with strategic relevance [1]. Inside the warehouse, order picking remains the most labour- and capital-intensive process, and two design decisions determine most of its outcomes: where each stock keeping unit (SKU) is stored, which is the slotting or storage location assignment decision, and how orders are retrieved, which covers the picking method, batching, routing and the technology that supports or replaces the picker. Smart warehouses add a layer of digital enablers, such as warehouse management systems with real-time data, Internet of Things sensing, autonomous mobile robots, wearable and augmented reality devices and digital twins [2, 3], which widens the design space and at the same time makes design errors more expensive.

The research literature approaches this design space from two sides. The first stream conceptualises Order Picking 4.0 as a socio-technical system and classifies digital technologies into those that support the human picker and those that substitute for the picker [4, 5]. The second stream formalises slotting as an optimisation problem and shows that policies which exploit product turnover together with order affinity can reduce retrieval time by up to 40% compared with turnover-based or class-based storage [6]. Both streams, however, treat slotting and picking largely in isolation, and review evidence points to a persistent gap between the assumptions of academic planning models and the practical factors that warehouse managers face [7]. What is missing is a managerial perspective: a way of designing slotting and picking together, under explicit organisational priorities, with the human factor and the digital enablers treated as design variables rather than as background conditions.

The problem is relevant for Ukrainian transport and logistics enterprises, for which competitiveness in the digital environment [8], sustainable development of the transport and logistics system [9] and continuity of cloud-based logistics services [10] have become managerial priorities during the wartime period and the coming recovery, while innovation management practices in transport systems are still being formed [11]. Warehouse modernisation projects in this context are capital-constrained, so the practical question is not which technology is the most advanced, but which combination of slotting and picking decisions gives the best balance of throughput, cost, quality and working conditions.

The aim of the article is to develop a managerial framework for the joint design of slotting and picking in smart warehouses and to demonstrate its decision logic with a stylised computational case.

2. Literature review

Winkelhaus et al. [4] define Order Picking 4.0 as a picking system in which physical and informational processes are integrated through digital technologies and derive a socio-technical framework in which technology, the human and the organisation carry equal weight. Grosse [5] applies content analysis to the literature on supportive and substitutive technologies in manual picking and concludes that the warehouse remains a socio-technical system whose technology effects must be assessed together with human outcomes, in the logic of Industry 5.0. Casella et al. [12] trace picking research from 2007 to 2022 and document a shift from routing and layout problems towards technology, automation and human factors. At the level of the whole facility, Zhen and Li [2] build a framework of smart warehouse operations management on information interconnection, equipment automation, process integration and environmental sustainability, and Tubis and Rohman [3] map the technologies of the intelligent warehouse in Industry 4.0. Kembro and Norrman [13] show empirically that retailers follow different paths from manual to smart warehousing and that the most labour-intensive processes, above all outbound picking, packing and sorting, are automated first. Smart warehousing therefore appears in the literature as a managed transition rather than a single technology choice.

The storage location assignment problem has a long optimisation tradition, but its managerial content has grown with the availability of order data. Mirzaei et al. [6] combine turnover and affinity information from historical orders in an integrated cluster allocation policy for parts-to-picker systems and validate it on a real warehouse data set. Zhuang et al. [14] optimise picking with rack-moving mobile robots and several workstations, where the assignment of racks and the sequencing of orders cannot be separated. Boysen et al. [15] review synchronisation problems in parts-to-picker warehouses and show that the right workstation set-up can raise throughput more than many well-researched planning tasks. Vanheusden et al. [7] classify nineteen practical factors of picking planning into four categories and demonstrate how they change the recommended policies. Together these works indicate that slotting is not a one-off optimisation but a recurring decision whose value depends on the picking system and on the data infrastructure.

Autonomous mobile robots have become the main vehicle of warehouse automation. Fragapane et al. [16] review their planning and control and stress the decentralisation of decision making, while Fragapane et al. [17] show how they increase flexibility and productivity in Industry 4.0 networks. Winkelhaus et al. [18] simulate hybrid order picking in which humans and autonomous robots share the same area and report gains in throughput and cost. The behavioural side of such systems is analysed by Lorson et al. [19], who link human-machine interactions across warehouse activities to behavioural issues and system performance. Grosse et al. [20] argue for a human-centric design of production and logistics systems in the transition from Industry 4.0 to Industry 5.0, and Setayesh et al. [21] identify eight human factors-related failure modes, including physical workload, fatigue, complexity and memory demand, that connect picking system design with pick errors. Winkelhaus et al. [22] find that work characteristics and job satisfaction change in Intralogistics 4.0, and De Lombaert et al. [23] show how order picker preferences can be elicited and integrated into the evaluation of job assignment mechanisms. Digital twins close the loop between design and operation: Rizqi et al. [24] propose a simulation-based digital twin for the smart warehouse, and Aretoulaki et al. [25] review discrete event simulation and digital twins in warehouse logistics.

The reviewed literature offers rich technology classifications, powerful slotting algorithms and growing evidence on human factors, but it rarely combines them into a managerial design logic that treats storage policy, picking method, technology profile and human-centric constraints as one decision system evaluated against a vector of performance indicators. This article addresses that gap.

3. Research objective, object and subject

The object of the research is the processes of storage location assignment and order picking in smart warehouses. The subject is the managerial design decisions on slotting and picking, their

interdependencies and the evaluation of alternative design configurations. The objective is to build a framework that structures the design decisions by management level, links them to a performance vector reflecting both economic and human-centric outcomes and supports the selection of a configuration under explicit managerial priorities. The tasks are to formalise the decision space, to specify an evaluation model, to compute the performance of alternative configurations for a stylised warehouse and to derive managerial implications.

4. Methods

4.1. Conceptual framework. Figure 1 presents the framework and Table 1 details the decision space. Design decisions are arranged in three layers. The strategic layer sets the automation level and the technology profile (supportive, hybrid or substitutive) together with the investment horizon. The tactical layer defines the storage policy (random, class-based, affinity-based or data-driven dynamic), the re-slotting cadence and the zoning of the picking area. The operational layer specifies the picking method (discrete, batch, zone-batch or goods-to-person), the batch size, the routing rule and the assignment of pickers to tasks. The layers are coupled: a storage policy pays off only if the picking method exploits it, and a substitutive technology changes the meaning of slotting from reducing picker travel to balancing workstation load. Two cross-cutting elements complete the framework. Digital enablers (warehouse management system, real-time data, digital twin) supply the information that makes data-driven slotting and simulation-based evaluation possible. Human-centric constraints (ergonomic load, error-prone task features, worker preferences) bound the set of admissible configurations [20, 21, 23]. All decisions are evaluated against a performance vector of five indicators: throughput, cost per order line, pick accuracy, ergonomic load and flexibility.

Table 1. Decision space of the managerial design of slotting and picking

Layer	Design variables	Alternatives considered in the case
Strategic	automation level and technology profile; investment horizon	supportive (RF terminal, pick-by-light, pick-by-voice, pick-by-vision); hybrid (human and AMR); substitutive (goods-to-person)
Tactical	storage policy; re-slotting cadence; zoning	random; class-based (ABC); affinity-based; data-driven dynamic; periodic or continuous re-slotting; single or multiple zones
Operational	picking method; batch size; routing rule; task assignment	discrete; batch (b orders per tour); zone-batch; goods-to-person; heuristic routing; rule-based or preference-aware assignment
Cross-cutting	digital enablers; human-centric constraints	WMS, real-time data, digital twin; ergonomic load limit, error-prone task features, worker preferences

Data source: own development based on [4, 5, 7, 20].

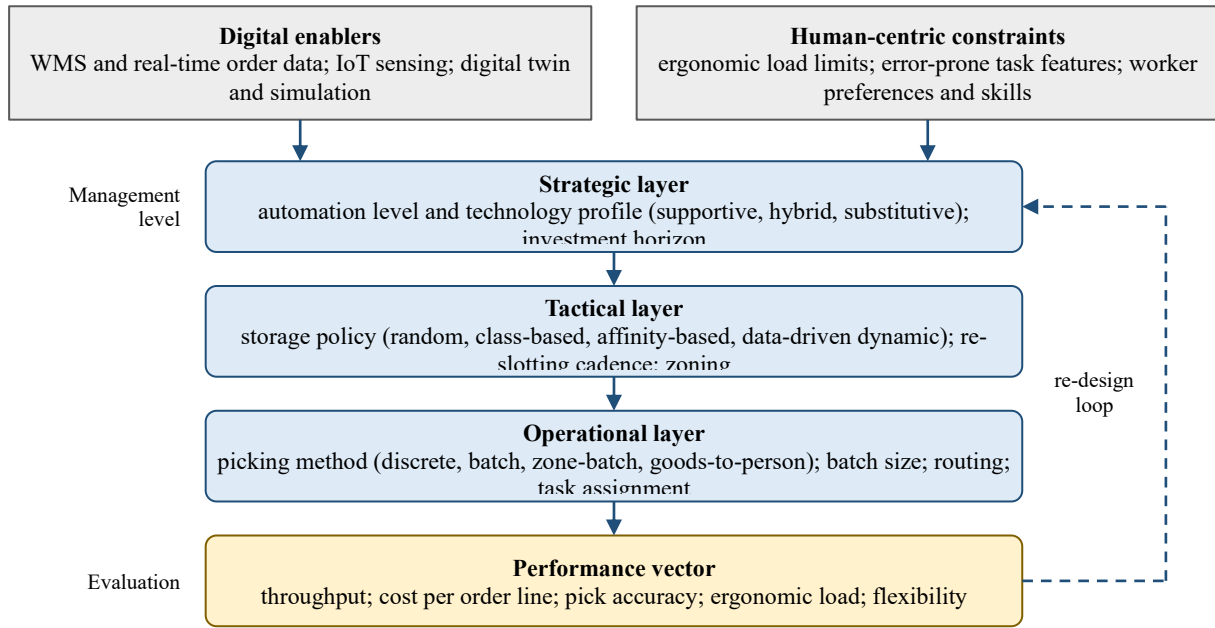


Figure 1. Conceptual framework of the managerial design of slotting and picking
Source of the figure: own development.

4.2. Decision cycle. Because demand profiles drift, the design is a closed loop (Figure 2). The cycle starts with the diagnosis of order data (SKU velocity, order affinity, order profile, error and workload records), proceeds to the generation of design alternatives as combinations of storage policy, picking method and technology profile, evaluates them with a simulation model or a digital twin [24, 25], selects a configuration with a utility function that encodes managerial priorities, implements and monitors it, and returns to diagnosis when a re-slotting trigger fires, for example when the SKU velocity ranking drifts beyond a tolerance.

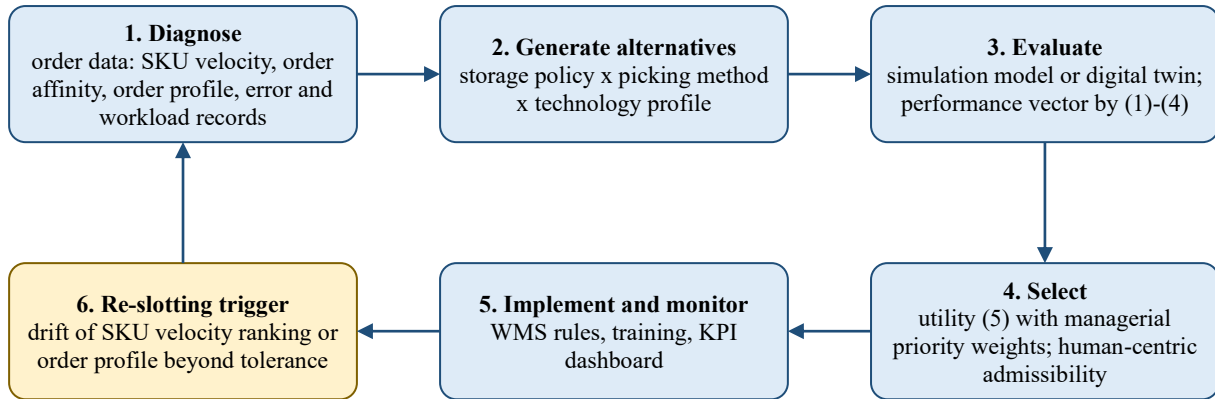


Figure 2. Decision cycle of the managerial design of slotting and picking
Source of the figure: own development.

4.3. Evaluation model. Let configuration k be described by the storage policy factor ρ_k (the ratio of picker travel to the travel under random storage), the picking method factor κ_k (the ratio of travel per order to the travel under discrete picking) and the technology parameters. The cycle time of one order, in seconds, is

$$T_k = \frac{t_s}{b_k} + n(t_p + t_{i,k} + \varphi_k t_c + \omega_k) + \frac{\rho_k \kappa_k D_0}{v} \quad (1)$$

where t_s is the tour set-up time, b_k the number of orders per tour, n the number of order lines, t_p the basic pick time per line, $t_{i,k}$ the information and verification time per line under technology k , $\varphi_k = 1$ if batch picking requires order consolidation and 0 otherwise, t_c the consolidation time per line, ω_k

the waiting time per line in goods-to-person systems, D_0 the travel distance per order under random storage and discrete picking and v the walking speed. For batch picking the travel factor is

$$\kappa_k = \frac{1+\lambda(b_k-1)}{b_k} \quad (2)$$

where λ is the relative growth of tour length per additional order in the batch. The throughput of one picker, in order lines per hour, is

$$Q_k = \frac{3600 n}{T_k} \quad (3)$$

The cost per order line combines labour, technology and quality costs:

$$C_k = \frac{w T_k}{3600 n} + a_k + e_k c_e \quad (4)$$

where w is the labour cost per hour, a_k the technology cost per line (investment and operating cost amortised over the annual number of lines), e_k the pick error rate and c_e the cost of one error. The ergonomic load index L_k and the flexibility index F_k , both on a scale from 0 to 1, are expert assessments of each configuration. The managerial utility of a configuration is a weighted sum of min-max normalised indicators:

$$U_k = \sum_{j=1}^m w_j \tilde{x}_{kj}, \quad \tilde{x}_{kj} = \frac{x_{kj} - \min_k x_{kj}}{\max_k x_{kj} - \min_k x_{kj}} \quad (5)$$

where $m = 5$ is the number of indicators, w_j are the priority weights of management and the normalised value is taken as the complement for cost-type indicators (cost per line, error rate, ergonomic load). Two priority profiles are compared: a cost-driven profile A ($w = 0.25, 0.40, 0.15, 0.10, 0.10$ for throughput, cost, accuracy, ergonomic load and flexibility) and a service- and human-centric profile B ($w = 0.20, 0.15, 0.25, 0.25, 0.15$).

4.4. Data of the stylised case. The parameters are not measured in a specific warehouse; they are set within the ranges typical of e-commerce picking discussed in the reviewed studies, so the results illustrate the decision logic rather than describe a particular enterprise. Six configurations are compared (Table 2). Common parameters: $n = 8$ lines per order; $t_s = 45$ s (5 s for goods-to-person); $t_p = 12$ s; $t_c = 3$ s; $D_0 = 360$ m; $v = 1$ m/s; $\lambda = 0.35$; $w = 12$ monetary units (m.u.) per hour; $c_e = 8$ m.u. per error. For the hybrid configuration K5 the travel factor is set directly at $\kappa = 0.35$, because the robot takes over the transport of totes and the picker moves only inside the zone.

Table 2. Design configurations of the stylised case and their parameters

Config.	Storage policy; picking method; technology	ρ_k	κ_k	$t_{i,k}$, s	ω_k , s	a_k , m.u.	e_k , %	L_k	F_k
K1	random storage; discrete picking; paper list or RF terminal (manual baseline)	1.00	1.00	8	0	0.00	0.80	0.80	0.80
K2	class-based (ABC) slotting; discrete picking; RF terminal	0.65	1.00	8	0	0.01	0.80	0.65	0.75
K3	class-based slotting; batch picking ($b = 4$); pick-by-light or pick-by-voice	0.65	0.51	5	0	0.03	0.40	0.55	0.70
K4	affinity-based slotting; batch picking ($b = 4$); pick-by-vision (AR glasses)	0.55	0.51	4	0	0.05	0.25	0.50	0.65
K5	data-driven dynamic re-slotting; zone-batch picking with AMR transport (hybrid human-robot)	0.50	0.35	5	0	0.12	0.25	0.35	0.70
K6	algorithmic pod slotting; goods-to-person picking (robotic mobile fulfilment system)	n/a	n/a	3	6	0.30	0.15	0.30	0.45

Data source: own development.

5. Results

Table 3 reports the performance of the six configurations. The manual baseline K1 achieves 51 order lines per picker-hour with travel taking 64% of the order cycle time. Class-based slotting alone (K2) raises throughput by 29% at a negligible technology cost, which confirms that slotting is the cheapest lever available to management. Combining class-based slotting with batch picking and a

supportive technology (K3) almost doubles the baseline throughput (99 lines per hour), affinity-based slotting with augmented reality (K4) reaches 109, the hybrid human-robot configuration (K5) 123 and the goods-to-person system (K6) 166 lines per hour, where picker travel disappears but waiting for pods appears.

Table 3. Performance of the design configurations (base labour rate and base volume)

Config .	T_k , s	Q_k , lines/h	Travel share, %	Labour, m.u./line	Technology, m.u./line	Quality, m.u./line	C_k , m.u./line	U_k profile A (rank)	U_k profile B (rank)
K1	565	51.0	64	0.235	0.000	0.064	0.299	0.266 (6)	0.212 (6)
K2	439	65.6	53	0.183	0.010	0.064	0.257	0.397 (5)	0.323 (5)
K3	291	98.9	41	0.121	0.030	0.032	0.183	0.712 (3)	0.617 (4)
K4	265	108.8	38	0.110	0.050	0.020	0.180	0.769 (1)	0.697 (3)
K5	234	122.9	27	0.098	0.120	0.020	0.238	0.732 (2)	0.776 (1)
K6	173	166.5	0	0.072	0.300	0.012	0.384	0.500 (4)	0.700 (2)

Data source: own calculations by formulas (1)-(5).

Figure 3 decomposes the cost per order line. The labour component falls monotonically from 0.235 to 0.072 m.u. per line, but the technology component grows faster than labour is saved once substitution begins: K4 and K3 have the lowest total cost (0.180 and 0.183 m.u. per line), the hybrid configuration K5 costs 0.238 m.u. and the goods-to-person system K6 0.384 m.u., which is 28% above the manual baseline. The quality component is small in absolute terms but differs by a factor of five between K1 and K6.

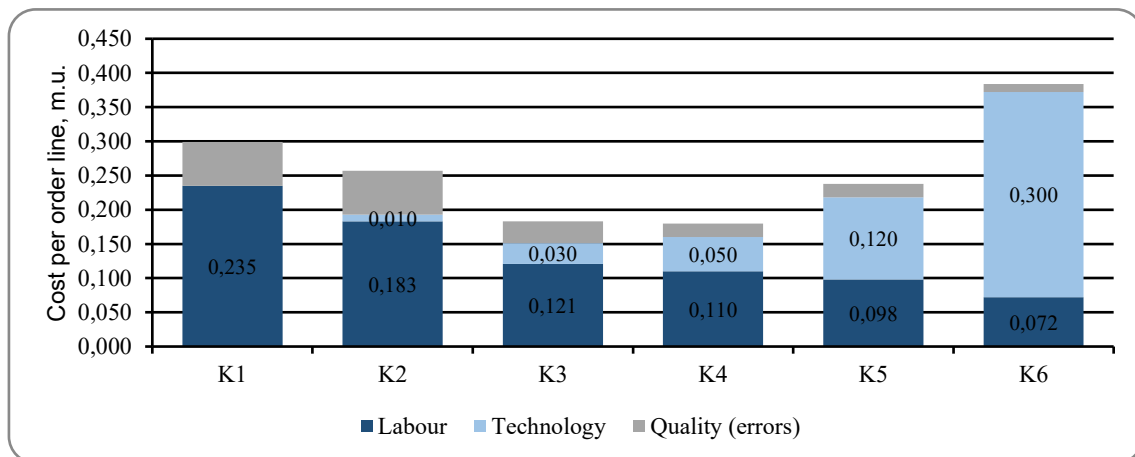


Figure 3. Structure of the cost per order line by configuration

Source of the figure: own calculations by formula (4).

Figure 4 compares the utility of the configurations under the two priority profiles. Under the cost-driven profile A the ranking is K4, K5, K3, K6, K2, K1; under the service- and human-centric profile B it is K5, K6, K4, K3, K2, K1. The same performance vector therefore produces a different preferred configuration depending on managerial priorities: profile A selects supportive technology with affinity-based slotting (K4), profile B selects the hybrid human-robot configuration (K5), and the goods-to-person system K6 moves from fourth to second place because its advantages in accuracy and ergonomic load receive a higher weight.

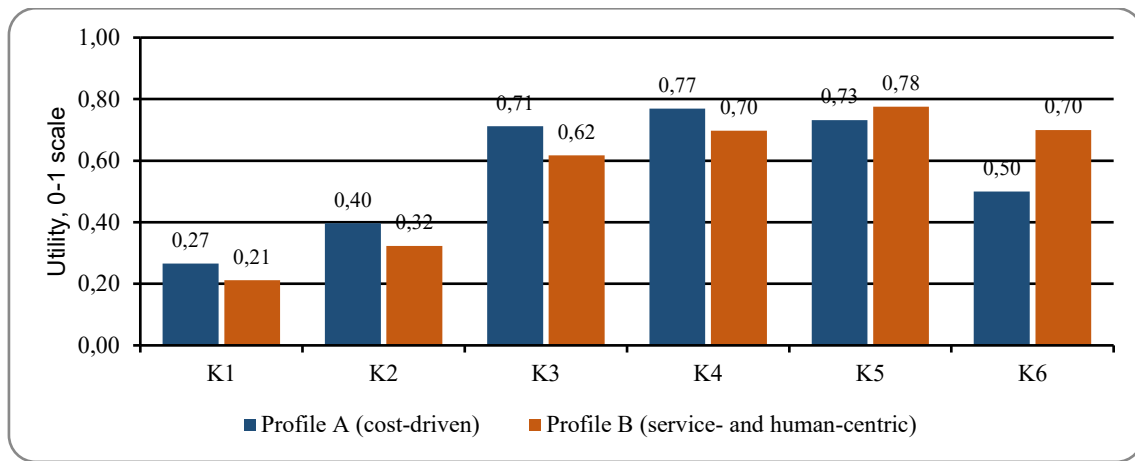


Figure 4. Managerial utility of the configurations under two priority profiles

Source of the figure: own calculations by formula (5).

Because the technology cost per line is investment-driven, it scales inversely with annual volume. Figure 5 plots the cost per line of K3 to K6 against multiples of the base volume, with the technology cost of K4 scaled in the same way. Hybrid picking (K5) reaches cost parity with K4 at about 5.5 times the base volume and the goods-to-person system (K6) at about 5.4 times; beyond that point K6 becomes the cheapest option. A rise in the labour rate alone would have to reach 66 to 76 m.u. per hour, more than five times the base rate, to produce the same effect. In the stylised case, volume rather than wage level is the variable that justifies substitutive automation.

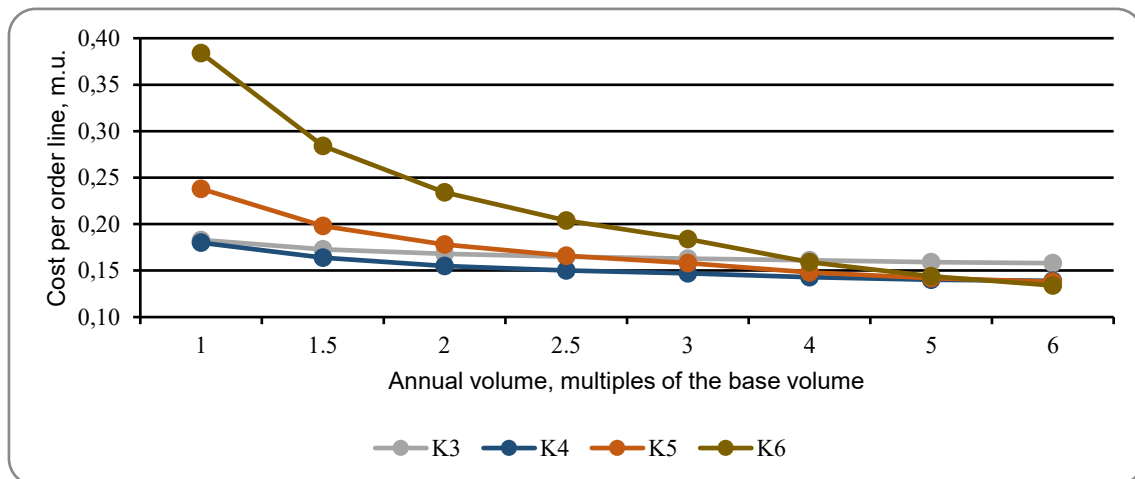


Figure 5. Sensitivity of the cost per order line to annual volume

Source of the figure: own calculations by formula (4).

6. Discussion

Four managerial implications follow from the framework and the case. First, the design decisions have a natural sequence. Data-driven slotting is the cheapest and fastest intervention and should precede any technology investment; supportive technologies combined with batch picking form the second step; hybrid human-robot picking and goods-to-person systems are justified only when the annual volume exceeds a threshold at which their investment-driven cost per line falls below that of the supportive configuration. This sequence agrees with the empirical observation that retailers automate the most labour-intensive outbound processes first [13] and with the evidence that AMR-based systems add flexibility when volumes grow [17].

Second, the preferred configuration is not a property of the technology but of the priority profile. The weights in formula (5) should therefore be made explicit and agreed with the owners of the warehouse strategy before the alternatives are compared, otherwise the design discussion turns into a technology preference contest. Third, human-centric constraints should act as admissibility filters rather than as an afterthought. The configurations K5 and K6 reduce the ergonomic load and the error rate, but they also change the content of work and the interaction between the picker and the machine

[19, 22], so the elicitation of worker preferences [23] and the analysis of error-prone task features [21] belong in the diagnosis stage of the cycle. Fourth, the evaluation stage should rely on a simulation model or a digital twin [24, 25], because the coupling between slotting and picking, congestion and the stochastic order profile cannot be captured by analytical formulas of the type (1) to (4) alone; the formulas are useful for screening, the twin for the final choice and for setting the re-slotting trigger.

For Ukrainian transport and logistics enterprises the implications are practical. Under capital constraints and workforce shortages the recommended path is to invest first in order data and slotting analytics, then in supportive picking technologies, keeping hybrid picking as a scalable option once volumes recover; this is consistent with the priorities of competitiveness in the digital environment [8], sustainable development [9] and continuity of cloud-based logistics services [10], and with the innovation management practices observed in transport systems [11].

The study has limitations. The parameters of the case are stylised, the model is deterministic and considers a single picker without congestion or blocking, the ergonomic and flexibility indices are expert assessments, and the technology cost is treated as fully investment-driven. Future research will calibrate the framework on the data of a Ukrainian third-party logistics warehouse, replace the analytical screening model by a stochastic simulation, include workforce learning effects and extend the utility function to preference-aware task assignment.

7. Conclusions

The article has proposed a managerial framework in which slotting and picking in smart warehouses are designed jointly, as a three-layer decision system coupled with digital enablers and human-centric constraints and closed into a decision cycle with a re-slotting trigger. An evaluation model that links the design variables to order cycle time, throughput, cost per order line and a weighted managerial utility has been formulated and applied to six configurations of a stylised warehouse. The results show that slotting is the cheapest lever, that supportive technologies combined with affinity-based slotting minimise the cost per order line, that hybrid and goods-to-person systems dominate on throughput and ergonomic load, and that their cost parity depends on volume rather than on the labour rate. The choice among the configurations follows from explicit managerial priorities, which is the core argument for treating the design of slotting and picking as a management task rather than as a technology selection.

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