Introducing Artificial Intelligence to Increase Efficiency in Warehouse Logistics: A Case Study

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Abstract

This paper examines how Artificial Intelligence (AI) forecasting and discrete-event simulation can support adaptive warehouse planning by integrating efficiency, workload balance, and operational resilience. Using distribution warehouse data, machine-learning models forecast daily delivery occurrence and order quantities, while simulation models represent warehouse processes, identify capacity constraints, and test staffing and layout scenarios. The results show that predictive analytics provides a stable basis for short-term planning, while simulation identifies order picking as the main operational bottleneck and the area of highest resource utilisation. The study contributes to cybernetic and systems-thinking research by operationalising an integrated planning workflow in which predictive feedback informs simulation-based experimentation and dynamic capacity alignment. The proposed framework integrates throughput, resource utilisation, workload distribution, and labour strain into a single adaptive planning approach. The paper offers a replicable analytical approach for researchers and practical guidance for managers seeking smoother workflows and more sustainable resource use.

Introduction

Modern distribution warehouses operate in increasingly unstable and demand-driven environments, where short-term fluctuations create operational inconsistencies (Albert et al., 2023). The case examined in this study illustrates this issue: a multinational corporation's distribution warehouse faces recurring cycles of overload and underload as daily store orders vary significantly. Similar patterns of fluctuating labour requirements in warehousing environments are documented in Popović et al. (2021).

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Because planning relies primarily on incoming orders rather than anticipatory forecasting, work is allocated reactively. The consequences of reactive operational planning: overtime peaks, idle periods, and inefficient labour allocation are consistent with findings in workforce scheduling research in logistics. Such workload oscillations have been linked to higher operational costs and adverse effects on employee satisfaction (Kumar et al., 2025).

This study, therefore, addresses a central research question: How can integrating artificial-intelligence-based predictive analytics with discrete-event simulation improve warehouse process efficiency while ensuring equitable workload distribution? The need to balance operational efficiency with workforce-related outcomes is increasingly recognised in socio-technical systems research (Kumar et al., 2025; Popović et al., 2021).

The research aims to design and validate an adaptive warehouse planning workflow that connects AI-based demand forecasting with simulation-based process evaluation. The study makes an integrative and empirical contribution by showing how predictive outputs can be translated into simulation scenarios, how these scenarios can reveal capacity constraints, and how the resulting evidence can support staffing, layout, and workload-balancing decisions. Grounded in a distribution warehouse case, the study addresses challenges widely observed in logistics operations, including demand volatility, labour pressure, and capacity misalignment.

Although grounded in a single organisational case, the study addresses challenges widely observed in distribution logistics: volatile demand, labour cost pressures, and difficulties retaining warehouse employees (Fuente et al., 2019). By integrating forecasting and simulation within a systems-thinking framework, the research highlights how technological interventions reshape the interactions between demand variability, capacity limitations, and human workload patterns in an approach consistent with systems analysis in logistics and operations management.

The case-study design necessarily imposes boundary conditions. Anonymity requirements and limited access to granular operational data, along with a modelling timeframe that restricts forecasting horizons to roughly one month, limit long-term generalizability.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on warehouse operations, demand forecasting, discrete-event simulation, and workforce equity, establishing the theoretical and methodological grounding for the study. Section 3 outlines the research design, describing the case context, data collection procedures, forecasting models, and simulation framework. Section 4 presents the empirical results of the forecasting analysis and simulation experiments, including bottleneck identification and scenario evaluation. Section 5 discusses the findings through a systems-thinking perspective, elaborates on the feasibility and highlights operational and workforce implications. Section 6 concludes by summarising contributions, acknowledging limitations, and proposing directions for future research.

Background

Warehouse Logistics and Performance Management

Warehouse logistics represents a critical dimension of supply chain management, serving as the operational interface between production and consumption (Gu et al., 2010; Roodbergen & Vis, 2009). The strategic importance of warehouses lies in their capacity to buffer supply-demand mismatches, maintain product availability, optimise inventory carrying costs, and facilitate rapid order fulfilment. Effective warehouse management requires simultaneous optimisation across multiple dimensions: cost minimisation, service level maintenance, space utilisation, and workforce productivity (Staudt et al., 2015).

Key performance indicators (KPIs) provide the quantitative framework for assessing warehouse operational health. Among the most significant metrics are order cycle time (the interval from order receipt to dispatch), order accuracy rate (percentage of complete, error-free shipments), fill rate (proportion of orders fulfilled in entirety), inventory turnover (ratio of goods sold to average inventory), and space utilisation efficiency (Richards, 2017). These metrics are conventionally termed SMART objectives (Selvik et al., 2021): Specific, Measurable, Attainable, Realistic, and Time-sensitive, ensuring that performance targets provide reliable data for trend analysis and continuous improvement initiatives.

Beyond traditional efficiency metrics, modern warehouse management increasingly incorporates human-centred KPIs, reflecting the recognition that workforce engagement and equity constitute essential components of sustainable operational performance (Romli et al., 2015). Metrics addressing work schedule predictability, equitable workload distribution, and employee satisfaction complement traditional productivity measures, acknowledging that unsustainable labour practices undermine long-term operational resilience.

Even though previous studies address warehouse performance, forecasting, simulation, and workforce planning separately, they do not fully provide an integrated decision-support approach that connects demand prediction, bottleneck identification, and workforce allocation within a single analytical framework.

Demand Forecasting in Warehouse Operations

Demand forecasting is a central mechanism for stabilising warehouse operations, enabling proactive planning of labour, inbound scheduling, and picking activities. In distribution environments, improved forecast accuracy is consistently associated with reductions in process variability and more effective resource utilisation (Eryilmaz, 2021)

Traditional forecasting approaches, such as exponential smoothing and ARIMA, remain widely applied due to their interpretability and suitability for relatively stable demand patterns (Hyndman & Athanasopoulos, 2018). However, these methods often underperform when confronted with nonlinear behaviour, intermittent demand, or promotional effects typical of warehouse environments (Kim et al., 2005).

Tree-based ensembles and neural network models can represent nonlinear interactions, complex seasonality, and heterogeneous demand drivers, typically achieving superior accuracy in logistics forecasts (Makridakis et al., 2020).

In practice, ML-based forecasts enhance decision-making for inbound coordination, order-picking capacity, and short-term workforce planning (Eichenseer et al., 2025).

Demand forecasts provide essential inputs for warehouse simulation models. When forecasted distributions are used as scenario drivers, simulation enables the evaluation of capacity constraints, bottlenecks, and alternative resource configurations under realistic operating conditions (Gu et al., 2010).

Although demand forecasting is widely recognised as relevant to warehouse planning, previous studies have not yet clearly demonstrated how forecast outputs can be integrated with simulation models to support bottleneck identification, resource configuration, and workforce allocation within a single decision-support framework.

Hybrid discrete-event and agent-based simulation

Hybrid discrete-event and agent-based simulation is a powerful methodological approach for analysing complex, stochastic warehouse systems. Unlike static analytical models, this hybrid approach enables the virtual reconstruction of operational processes by combining the strengths of discrete-event simulation (DES) and agent-based modelling (ABS). This integration captures queueing behaviour, resource contention, temporal variability, and individual-agent decision-making that characterise real warehouse environments (Agalianos et al., 2020).

The hybrid simulation paradigm is particularly well-suited for warehouse modelling because it addresses both process-level and agent-level dynamics simultaneously. While the discrete-event component tracks material flow, queue formation, and event-driven state changes, the agent-based component models autonomous entities such as workers, forklifts, and vehicles with individual attributes, decision rules, and behavioural patterns.

Hybrid simulation further enables comprehensive sensitivity and scenario analysis. Managers can systematically test how modifications in staffing levels, agent behaviour rules, equipment performance, order profiles, or layout configurations influence both individual agent performance and system-wide stability and service levels (Pudleiner & Colton, 2015). The researchers fail to adequately connect predictive demand signals with simulation-based capacity testing, so that managers can anticipate bottlenecks and adjust staffing, layout, and workload distribution before operational pressure materialises.

Integration of Forecasting and Simulation: Research Gap and Conceptual Framework

The literature review identifies three relevant streams for adaptive warehouse planning. The first stream focuses on warehouse performance measurement, where throughput, space utilisation, order accuracy, and labour productivity remain central indicators (Staudt et al., 2015). A more recent extension of this stream incorporates human-centred indicators such as workload distribution, schedule predictability, and labour strain

(Popović et al., 2021). The second stream examines demand forecasting, where machine-learning models support short-term anticipation of delivery occurrence, delivery quantities, and labour requirements (Hyndman & Athanasopoulos, 2018). The third stream applies discrete event simulation to evaluate process flows, capacity constraints, bottlenecks, and alternative resource configurations (AnyLogic, 2020).

Our reading of these streams suggests that their combined decision-support potential remains underdeveloped. Forecasting studies commonly emphasise predictive accuracy, while simulation studies commonly examine warehouse performance under predefined scenarios. A clear planning logic is still needed to explain how forecast outputs can become simulation inputs, how simulated bottlenecks can inform operational decisions, and how efficiency indicators can be assessed together with workload implications.

This study addresses the research gap by operationalising an integrated forecasting-simulation workflow in a distribution warehouse case. The framework links predictive feedback, simulation-based experimentation, capacity alignment, and workload assessment. It thereby provides a systems-oriented planning approach in which demand anticipation is connected to process evaluation and adaptive managerial decision-making.

Methodology

The research approach is predicated on a case study of goods delivered to a warehouse. Based on this data, a short-term prediction of new deliveries and a simulation of warehouse processes were created.

To predict deliveries, a two-stage predictive model was developed. In the initial phase, the model forecasts the likelihood of a shipment's arrival on a specified date. In the subsequent phase, it calculates the anticipated quantity of items that are expected to arrive at the warehouse.

In the next step, a simulation of warehouse processes was created based on the floor plan and operational information. The simulation replicates the operational processes observed in the physical warehouse, albeit with fewer products.

Data sources

The data obtained from the company comprised operational records spanning April 2019 to March 2025 for a single product line. The dataset encompassed three primary components: product delivery specifications (including delivery quantity and expected delivery date), warehouse operational metrics, and a detailed floor plan of the facility. These elements were essential for establishing the temporal and spatial parameters required to construct realistic simulation scenarios.

Data Preparation for Forecasting Model

The preparation of data for the forecasting model was of paramount importance, as the data from the period in question exhibited inconsistencies due to disruptions caused by the novel Coronavirus disease (2019) pandemic.

The historical data set spanned from April 2019 to March 2025. Due to significant disruptions in product supply caused by the pandemic, forecasts were revised. Consequently, it was determined that the final analysis would be based exclusively on data collected from March 17, 2023, onward. This date marks the commencement of regular product deliveries and provides sufficient data inputs for model training.

The model training was executed on data spanning from March 17, 2023, to March 10, 2025. To verify the forecast's accuracy, the week from March 10 to March 17, 2025, was omitted from the analysis. Subsequently, the control data were utilised to evaluate the adequacy and accuracy of the forecasting model.

Data Table Structure

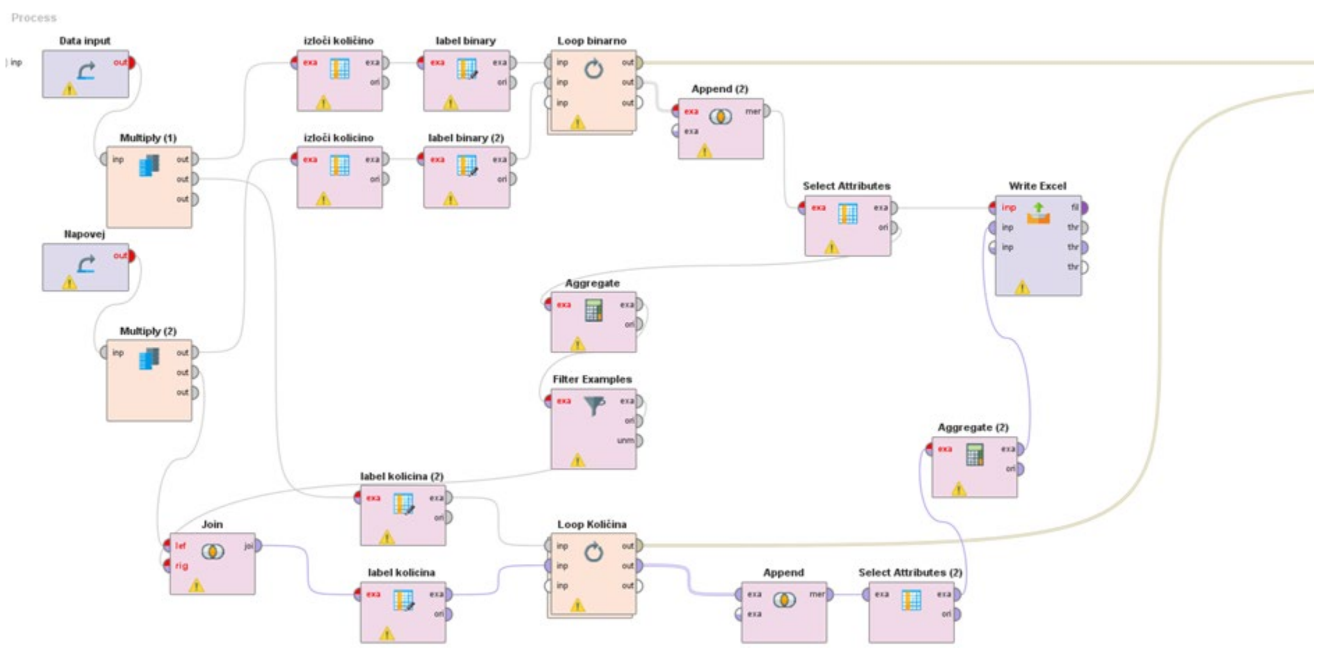
Ensuring the successful training of the predictive model required adequate data preparation and structuring. This approach was adopted to maximise the extraction of pertinent information from the data, thereby ensuring the accuracy and reliability of the predictions.

The data table contained the following columns: delivery date; Delivered, quantity; year; month; week; day of the week; working day or weekend; days since the preceding delivery; The average quantity of products received in the past seven days; The number of deliveries in the past seven days; history of delivery for the last 30 days (30 columns)

Data Mining Process

Data mining process was predicted by a predictive model implemented in the RapidMiner (Altair AI studio) (Altair, 2025) software environment. This environment is a comprehensive suite of tools designed to facilitate data mining and analysis. The components depicted in Figure 1 were utilised in the predictive process.

Figure 1
Prediction process in RapidMiner



Source: Authors

As depicted in Figure 1, the process commences with the Retrieve Data Input building block, which serves as the source of training data for the model. This component is connected to the Multiply component (1). For binary prediction, the initial output of this component is linked to the Select Quantity component (of the Select Attributes type), in which all data, except the quantity of delivered products, persists throughout the process.

The Select Quantity component is linked to the Label binary component (of the Label type), where the delivery's binary value serves as the target variable predicted from the delivery date. From this point onward, the component is linked to the Loop binary component (of type Loop), which is configured to reiterate the process internally 50 times.

Within the Loop component, a process is built in which the data used for learning binary predictions is derived from the first input, and the data used for prediction is derived from the second input. The training data is passed to the Deep Learning block, which contains a model that learns from it. The Deep Learning block is connected to the Apply Model block, which has two inputs: the first receives the trained model, and the second receives the prediction data. The output of this block represents a binary prediction – on which day the product will be delivered. The prediction is passed to the Performance component, which evaluates its accuracy.

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The Performance component has two outputs. The initial output shows the accuracy rating and corresponds to the Loop component's output, as shown in the final program output. The second output is designated for subsequent processing and is associated with the Loop component's second output. In the forecasting process, the Apply Model component received data from the second input of the Loop component, which was obtained from the Retrieve Forecast component. This data was processed in a manner consistent with the training data, thereby ensuring the integrity and consistency of the tables. The process is then advanced at the second output of the Loop binary component, where data from 50 iterations is transferred to the Append component. This component consolidates all 50 predictions into a single table, streamlining processing and analysis. The amalgamation of these data elements is then transferred to the Select Attributes component, where a specific set of attributes is selected, including the date, the binary prediction, the confidence level, and the actual binary value.

After the initial output from this component, the designated data is directed to the Write Excel component, which generates a table containing the results upon completion of the process. Subsequently, the selected data is transferred to the Aggregate component, where the average confidence value is calculated from all 50 predictions. Consequently, a single prediction is derived from a set of fifty predictions, thereby representing the mean of all predictions.

This predicted value is then passed to the Filter Examples component, where the condition is set to require Confidence to be greater than or equal to 0.5. This value is selected because confidence is measured on an interval from 0 to 1, with values above 0.5 indicating sufficient confidence in the prediction.

Based on the predicted delivery date of the shipment, expected between March 10, 2025, and March 17, 2025, the quantity of products arriving at the warehouse is estimated.

The training data for forecasting the quantity is derived from the Multiply 1 component. This data is subsequently transferred to the "Label quantity 2" component, where it is used to forecast quantity based on the delivery date. The marked data is transferred to the first input of the Loop quantity component, while the second input receives the forecast data from the Multiply 2 component. This data was combined with the forecast binary data from the Filter component in the Join component.

Within the Join component, the data is integrated to ensure that the dates for which the quantity is predicted align with the dates from the binary prediction. The data is subsequently transferred to the Label component, where it is determined that the target variable is the quantity predicted based on the date. This data extends to the second input of the Loop quantity component, which is constructed similarly to the Loop binary component.

The initial output of the Performance component is associated with the process data output. The second output consists of the 50 predicted data points, which are directed to the Append component. In this component, all predictions are consolidated into a unified table. The amalgamated table is subsequently transferred to the Select Attributes component, where the data is filtered based on specific criteria, including date, actual quantity, and predicted quantity.
Subsequently, this data is transferred to the Aggregate 2 component, where the following calculations are performed: The following quantities are calculated:

- The arithmetic mean of the predicted values
- The minimum predicted value
- The maximum predicted value

This data is associated with the Write Excel component, which generates an Excel table containing a processed forecast of whether the shipment will be delivered and the number of products expected to be delivered.

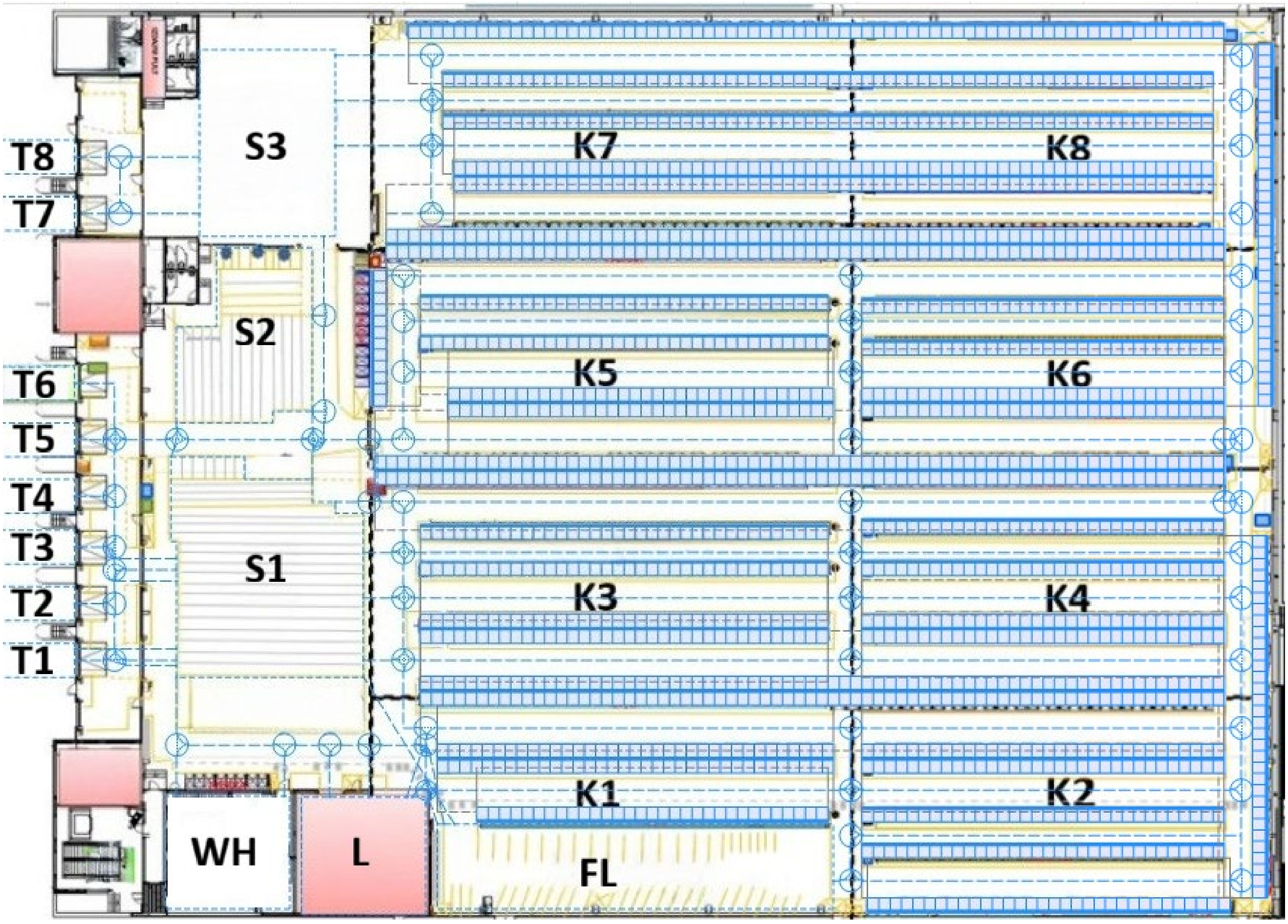
Warehouse Simulation Model in AnyLogic

A working warehouse simulation model was designed in AnyLogic (2020), based on the floor plan and information about the warehouse operations. To facilitate visualisation of the process and its subsequent tracking, the simulation was divided into 4 distinct thematic sections: floorplan description, delivery process, internal movement of goods, preparation of shipments, and Shipping process.

Floorplan Description

The simulation layout was based on the floor plan of the existing distribution warehouse, as illustrated in Figure 2.

Figure 2
Warehouse floor plan used in simulation



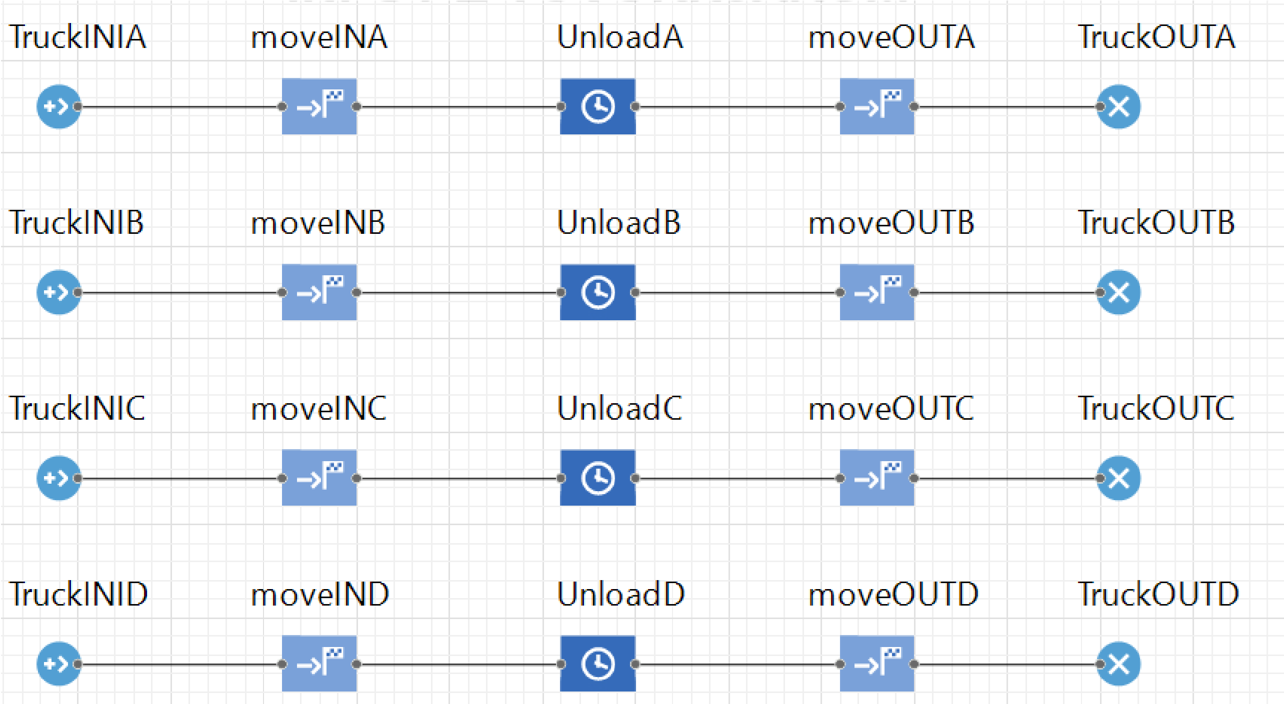
Source: Authors

The layout consists of zones representing specific locations within the warehouse where operational processes occur or where transport agents are initially positioned. The simulation zones are interconnected by dashed lines, which denote the routes along which agents can move. The simulation input comprises regular time-based product deliveries occurring at the warehouse locations designated as T1 to T4. The S1 zone is where products arriving through the inbound zones are unloaded. Whenever product relabelling is required, this process is conducted in the L zone. The storage zone comprises 3,306 cells, formed by back-to-back and one-sided storage racks designated K1-K8. The zones where commissioned products are consolidated and prepared for dispatch are indicated as S2 and S3. The zones labelled T5 to T8 serve as the shipping areas, which also constitute the exit points of the simulation model. The zone marked WH serves as the origin point for all transport agents referred to as Worker, while the zone marked FL serves as the origin point for all transport agents referred to as Forklift.

Delivery Process

The delivery process, which represents the product inflow into the simulation model, comprises four distinct sub-processes. These processes are illustrated in Figure 3.

Figure 3
Delivery process into the warehouse



Source: Authors

Each process commences at the origin zone, TruckIN, whereby a transport agent named Truck is created. Each process generates a single transport agent that delivers one product batch. The inbound products are agents designated as ProductA, ProductB, ProductC, and ProductD.

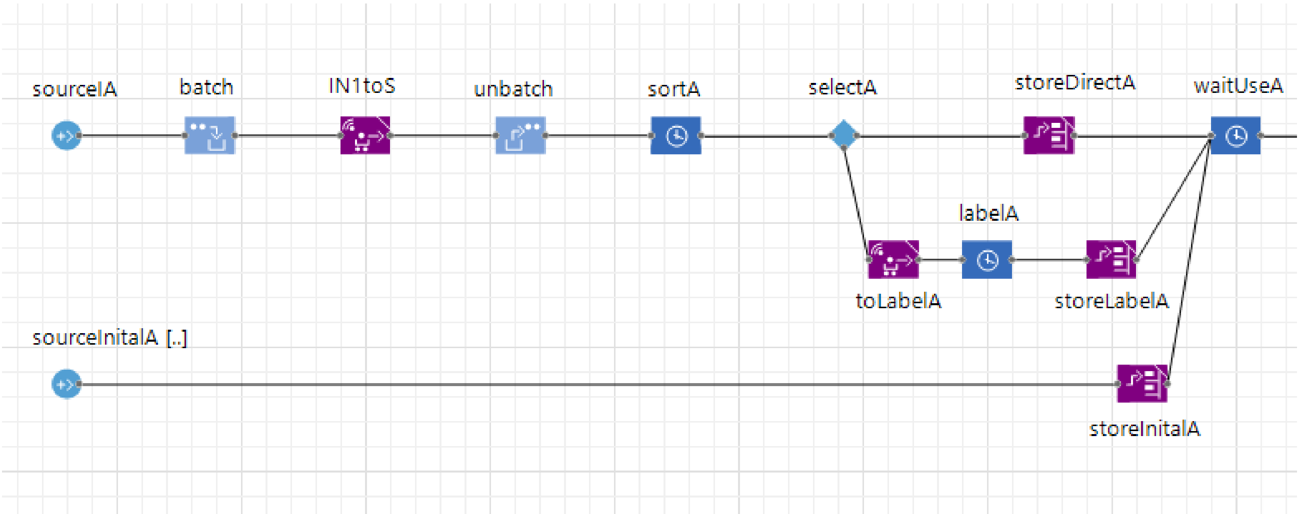
The process initiates with the block TruckIN, which is executed in the zone TruckIN, resulting in the creation of a transport agent Truck. Following this, the block moveIN transports the agent from the zone TruckIN to the delivery zone. The transport process for product A arrives at zone T1; the process for product B arrives at zone T2; the process for product C arrives at zone T3; and the process for product D arrives at zone T4. Within the simulation model, the product delivery process is triggered twice per simulation day.

Following the relocation of the transport agent, the unloading process commences, as illustrated by the block Unload. The unloading duration is set at 60 minutes. At this moment, product agents are created and subsequently manipulated in the following processes. This is facilitated by an inject function that generates a new agent when a specified condition is satisfied. Upon completion of the unloading duration, the process continues with the block moveOUT, which relocates the transport agent from zone T to zone TruckOUT. At this location, the agent ceases to influence the simulation model and is removed, as indicated by the TruckOUT block.

Internal Movement of Goods

Figure 4 illustrates the manipulation process for product A and the stocking of storage spaces with an initial inventory of product A, which is representative of the processes for products B, C, and D, as all are identically structured.

Figure 4
Manipulation process for product A



Source: Authors

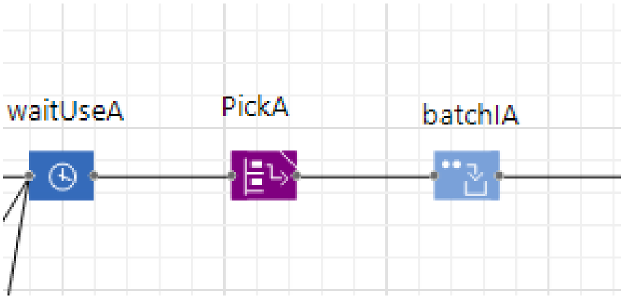
Upon initialisation of the simulation model, the block sourceIA creates 100 agents of product A, which independently relocate to storage racks via the block storeInitialA. After that, they await utilisation in the picking process, represented by the block waitUseA. The block from the delivery process, using an inject function, inserts 10 agents of product A at the process origin point. The process commences at zone T1, where the block batch is executed, consolidating the 10 agents into a single entity. This operation serves to represent all products as palletised units, which also aligns with the actual warehouse operations, as individual products are not delivered separately packaged.

The block IN1toS uses the transport agent ForkLift to move the product A agent from zone T1 to zone S1. In zone S1, the block unbatch is executed, representing the unloading of products delivered to the warehouse. Within this block, a single product agent is decomposed back into 10 product A agents. The subsequent block, sortA, is executed in zone S1 and involves inspecting products to determine whether relabelling with linguistically appropriate labels is required. The block sortA is executed for 10 minutes. The subsequent block selectA is a decision block containing a function that routes 50% of products to a process in which products are stored directly, and 50% to a process in which labels are modified. In instances where products proceed directly to storage, the procedure continues with the block storeDirectA, where the transport agent ForkLift relocates the product A agent from zone S1 to one of the storage zones K1–K8. When a product is routed to the relabelling process, the block toLabelA transports it via the transport agent ForkLift from zone S1 to zone L, where the subsequent block labelA represents the relabelling procedure, which has a duration of 30 minutes. Upon completion of the relabelling duration, the process continues with the block storeLabelA, which relocates the product A agent via the transport agent ForkLift from zone S1 to one of the zones K1–K8. Both process pathways converge at the block waitUseA, which represents the average time a product spends awaiting utilisation in storage and is configured to 1 hour due to the limited product quantity.

Preparation of Shipments

Figure 5 illustrates the continuation of the process for product A, which awaits further processing. Upon expiration of the waiting period, the picking process commences, utilising the block PickA. This process is executed across the entire storage rack zone, with transport agents designated as Workers performing this function. The block PickA, via transport agents, relocates the product A agent from its assigned cell within the storage zone to zone S3. Through the processes for products B, C, and D, product B is relocated to zone S3, whilst products C and D are relocated to zone S2. This process represents the manual picking operation conducted by warehouse personnel. Following the picking operation, it is necessary to consolidate individual products into shipments, which constitute the warehouse exit. This commences by combining multiple products utilising the block batch I, which is executed in zone S2 or S3, depending on the assigned zone for each product.

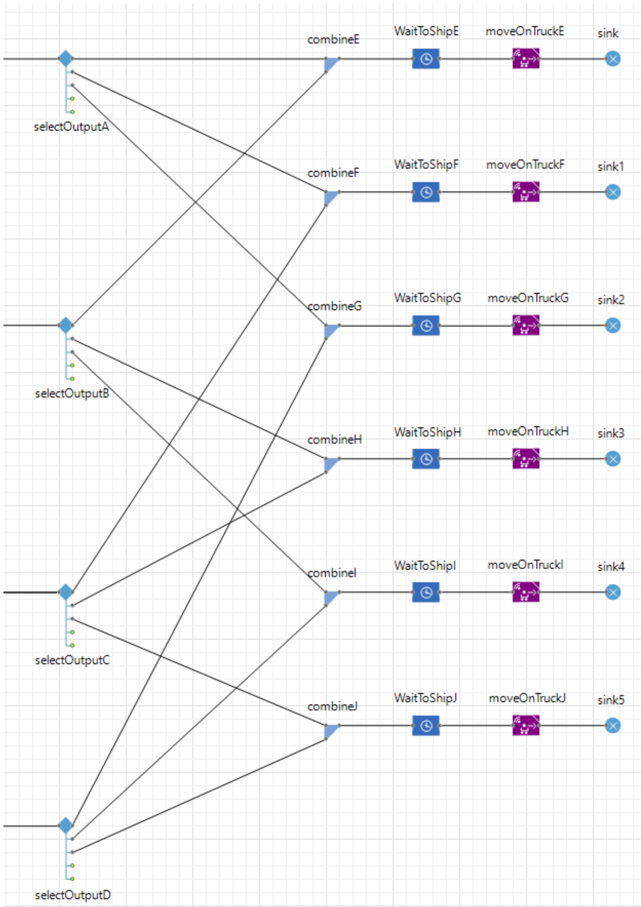
Figure 5
Continuation of the process for product A



Source: Authors

In actual distribution warehouses, shipments are not prepared containing only a single product type. Rather, multiple product types are consolidated into a single shipment. This process is illustrated in Figure 6, which demonstrates how individual picked products are combined into new shipments. This continuation of the previously described process is represented by the block selectOutput, which contains a function that routes products to the subsequent process with a 33.33% probability. Consequently, product A has an equal probability of being directed to the process for the creation of products E, F, and G. Through this process, products are consolidated in the blocks combine, which generate the following combinations: in combineE, products A and B are merged; in combineF, products A and C are merged; in combineG, products A and D are merged; in combineH, products B and C are merged; in combineI, products B and D are merged; and in combineJ, products C and D are merged. The process can proceed only once both agents have arrived at the combine block to generate a new agent, which then continues the process. Following the combine block, the newly created agent awaits dispatch, as indicated by the block WaitToShip in the assigned zones S2 and S3. When the process reaches the block WaitToShip, a function is triggered, notifying the shipping process that dispatch from the warehouse may commence. This block halts the process until the shipment arrives at its assigned dispatch zone, designated T5-T8. Once this condition is satisfied, the process continues with the block moveOnTruck, in which the transport agent Forklift relocates the product agent from its assigned zone to the location where the transport agent Truck is positioned. This segment of the process illustrates the relocation of the shipment from the warehouse holding zone to the outbound truck.

Figure 6
Combination of products

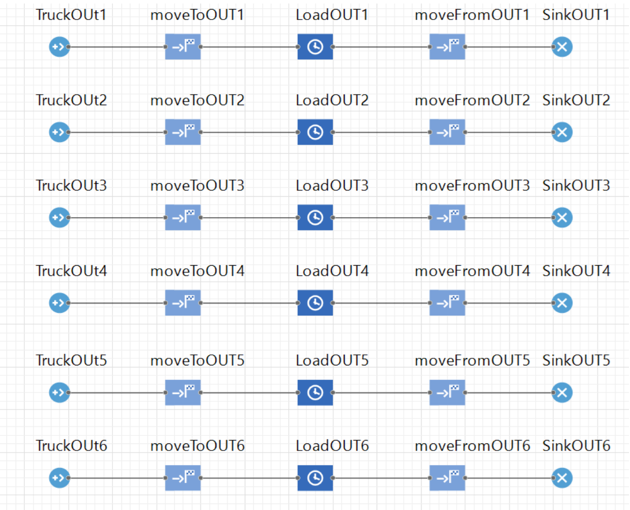


Source: Authors

Shipping Process

The shipping process illustrated in Figure 7 commences when the block WaitToShip, via an integrated function, initiates the product dispatch process. The process described here for TruckOUT1 is representative of all other processes, with the sole difference being the designated dispatch zone. Upon activation of the process, a transport agent is created at the RoadIn zone, as represented by the block TruckOUT1. The subsequent block moveToOUT1 relocates the transport agent Truck from zone RoadIN to zone T5, which constitutes its assigned dispatch zone for product E. When the transport agent arrives at the assigned zone, the process continues with the block LoadOUT1, which represents the loading time for the transported product. The process can proceed only once the loading operation is complete, as signalled by the block moveOnTruck, illustrated in Figure 6. This signal is transmitted to this process upon completion of the relocation of the product agent. Upon receipt of the continuation signal, the transport agent Truck is relocated from its assigned zone T5 to zone RoadOut, as a consequence of the block moveFromOUT. The conclusion of the process and the transport agent's exit from the simulation are represented by the SinkOUT block.

Figure 7
Shipment process



Source: Authors

Results and Findings

Delivery Dates Prediction

The forecasting model has been developed primarily to accurately predict whether items will be delivered on a specific day of the week. The forecast period runs from March 10 to March 17, 2025. Upon delivery, the model predicts a value of 1; if delivery is unsuccessful, it predicts 0. The results of the first phase of the forecasting model yielded binary predictions for the period from 10 March to 17 March 2025, which are presented in Table 1.

When comparing the forecast results with actual delivery dates, it is evident that the forecasting model successfully predicted delivery dates. The dates predicted by the binary component of the model were 10 March, 14 March, and 17 March, with confidence levels of 95%, 66%, and 73%, respectively. The other dates were predicted as no delivery. The overall confidence ranged from 58% to 99%.

Table 1
Prediction on the delivery dates

Date	Binary yes/no delivery	Average binary yes/no prediction	Confidence level
10/03/2025	1	1.00	95 %
11/03/2025	0	0.64	58 %
12/03/2025	0	0.00	97 %
13/03/2025	0	0.34	68 %
14/03/2025	1	1.00	66 %
15/03/2025	0	0.00	99 %
16/03/2025	0	0.10	84 %
17/03/2025	1	0.96	73 %

Source: Authors

Forecasting the Quantity of Delivered Products

In the second phase of the forecasting model, delivery quantity predictions for the warehouse were made based on the forecasted dates. For each forecasted delivery date, 50 forecasting iterations were executed, and the resulting data are presented in Table 2, which includes the minimum forecasted quantity, the Average forecasted quantity, the maximum forecasted quantity, and the percentage deviation of each value from the actual delivered quantity.

For the delivery date of 10 March, 3024 units were delivered; the maximum forecasted quantity was 2,830 units, representing a deviation of 6.42%. For the 14 March delivery date, the maximum forecast quantity was 1,672 units, representing a 41.46% deviation. For the delivery date of 17 March, 2,184 units were delivered; the maximum forecasted quantity was 2,085 units, representing a deviation of 4.53%. This demonstrates that the maximum forecasted quantities were most accurate, whilst the minimum forecasted quantities were least accurate.

Table 2
Predicting delivery quantities

Forecast date	Quantity delivered	Minimum forecast quantity	Average forecast quantity	Maximum forecast quantity	% deviation from minimum delivered quantity	% deviation from average forecast quantity	% deviation from maximum forecast quantity	Forecast range
10/03/2025	3,024.0	1,548.0	2,120.7	2830.0	48.81 %	29.87 %	6.42 %	1,282.0
14/03/2025	2,856.0	514.0	1,169.1	1672.0	82.00%	59.06 %	41.46 %	1,158.0
17/03/2025	2,184.0	934.0	1,541.8	2085.0	57.23%	29.40 %	4.53 %	1,151.0

Source: Authors

Warehouse Processes Simulation

The simulation model ran for 7 simulation days, during which 14 deliveries were expected; however, no product received the anticipated number of deliveries, as evidenced in Table 3. Product A received the most deliveries, with 17, whilst product C received the fewest, with 13. All products, except product C, received more deliveries than anticipated. Through the select block, all products entering the warehouse via delivery demonstrated complete throughput. At the select block, the probability of routing products to either the direct storage process or the relabelling process was 50%; in this regard, product B demonstrated the greatest accuracy, with appropriate product routing distribution. The greatest deviation was observed for product D, with 68 products routed to direct storage and 82 routed to relabelling.

Upon reaching the point in the process where products are picked from storage racks, a bottleneck is identified: products A to D are picked in batches of 4 to 8.

Table 3
Simulation results from delivery to picking

Product	Number of deliveries	Number of products arriving at the select block	Number of products stored directly on racks	Number of products sent for relabelling	Number of products picked	Percentage of products picked
A	17	170	86	84	8	4,70 %
B	16	160	80	80	6	3,75 %
C	13	130	68	62	4	3,07 %
D	15	150	68	82	6	4,00 %

Source: Authors

Following the picking process, the four base products are consolidated into new products designated for dispatch from the warehouse; Table 4 presents the numerical results of creating new products and dispatching them from the warehouse. In the simulation model, product G was produced in the greatest quantity, with 3 units, followed by product E with 2 units, and products F, H, and I with 1 unit each, whilst no units of product J were produced. Of all products created, the processes for products E, F, G, and H were completed, indicating that they were loaded onto the transport agent *Truck* and that the truck dispatch was successful. Product: I remained in the loading process at the conclusion of the simulation.

Table 4
Simulation results from the creation of products to shipping

Product	Number of products created	Number of successful relocations to truck	Successful truck dispatches
E	2	2	2
F	1	1	1
G	3	3	3
H	1	1	1
I	1	0	0
J	0	0	0

Source: Authors

The utilisation of transport agents is presented in Table 5, where the processes for products are consolidated into blocks that perform relocations. The use of transport agents in the process from product arrival in the warehouse to storage is minimal; at the conclusion of the simulation, all transport agents were idle, the utilisation rate was low, and the request queue was zero.

The transport agents designated for picking operations are presented in Table 5 under "WorkersPick". At the conclusion of the simulation, no agent remained idle, as evidenced by a utilisation rate of 94.4%, indicating substantial occupancy. Individual transport agents at this stage of the simulation had between 214 and 243 outstanding requests at the conclusion of the simulation. Subsequent processes demonstrate low utilisation rates ranging from 0 to 0.497%, a consequence of the low throughput in the picking process, which can thus be identified as the warehouse bottleneck.

Table 5
Resources utilization after simulation

	Number of transporters	Idle transporters	Transporter Utilisation (%)	Requests
ForkLiftINtoS	4	4	0,1	0
ForkLiftStoragestoreDirect	3	3	0.5 – 0.7	0
MovetoLabel	12	12	4.5 – 7.4	0
ForkLiftStoragestoreLabel	3	2 - 3	1.0 – 3.1	0
WorkersPick	12	0	94.4	214 - 243
ForkLiftOutmoveOnTruck	2	2	0 - 0.497	0

Source: Authors

Discussion

The findings show how forecasting and simulation can be combined to support adaptive warehouse planning. The forecasting component provides short-term information about expected delivery occurrence and quantities, while the simulation component translates these expectations into process-level consequences. This connection is central to the proposed planning workflow because it allows managers to move from demand anticipation to capacity evaluation and operational adjustment.

The forecasting results indicate that delivery occurrence can be anticipated with sufficient accuracy to support short-term planning. This is operationally relevant because binary delivery forecasts help managers identify days on which warehouse activity is likely to increase. Quantity forecasts provide an additional planning signal, though their interpretation requires caution because greater variability in the input data reduces prediction precision. For managerial use, the forecasting model should therefore be treated as a planning aid that indicates expected workload pressure.

The simulation results clarify where forecasted workload pressure becomes operationally critical. The main constraint occurs in the picking process, where worker utilisation reaches its highest level, and request queues accumulate. In contrast, inbound transport, storage, movement, labelling, and outbound movement show substantially lower utilisation. This imbalance indicates that the warehouse challenge is primarily a capacity-alignment issue across activities rather than a general shortage of all resources. From a systems-thinking perspective, the picking process serves as a leverage point: improvements in this stage can increase downstream flow, reduce shipment delays, and limit stock accumulation in the racking system.

These findings provide concrete implications for warehouse managers. Daily delivery forecasts can be used to prepare staffing plans before operational pressure materialises. On forecasted peak days, managers can assign additional workers to picking, postpone non-urgent labelling or replenishment tasks, and organise temporary support before queues increase. The simulation results also support cross-training decisions, as employees from less-loaded activities can be prepared to assist with picking during peak periods. In addition, managers can use the simulation model to test layout and process changes before implementation, such as relocating high-frequency items closer to staging areas, revising picking routes, introducing batch or wave picking, or expanding temporary staging space.

The integrated workflow also has implications for labour strain and workload balance. Predictive information gives managers more time to distribute demanding tasks across shifts, reduce last-minute overtime, and improve schedule predictability. Simulation then makes visible where labour pressure is likely to concentrate. Together, forecasting and simulation support a feedback-oriented planning routine in which expected demand is forecast, operational feasibility is tested, bottlenecks are identified, and staffing or layout decisions are adjusted before the warehouse reaches overload.

Conclusion

This research demonstrates that the systematic integration of artificial intelligence predictive analytics with discrete-event simulation provides a powerful framework for warehouse process optimisation that simultaneously addresses operational efficiency and workforce equity objectives. Through an empirical case study, the research shows that the forecasting model correctly identified the observed demand dates during the validation period, while quantity prediction errors ranged from 4.53% to 41.46%. The demand forecast was combined with simulation-based bottleneck identification, enabling targeted operational improvements and more predictable workforce scheduling.

The research contributes to logistics management literature by demonstrating that forecasting and simulation, typically employed independently, generate substantial synergistic value when systematically integrated. The approach transitions warehouse management from reactive crisis response to proactive capability alignment, enabling planning, resource optimisation, and scenario evaluation. Critically, the research elevates workforce equity to co-objective status alongside traditional efficiency metrics, demonstrating that human-centred considerations and operational excellence are complementary rather than contradictory objectives.

From a practical perspective, the methodology and tools employed, RapidMiner for forecasting, AnyLogic for simulation, are commercially available and technically accessible to organisations of varying technological sophistication. This accessibility suggests that the proposed approach is an implementable solution that addresses recognised challenges in warehouse management practice.

As supply chains navigate increasingly complex and volatile market environments, the demand for more sophisticated planning methodologies intensifies. This research demonstrates that advanced analytics and simulation capabilities, properly integrated and implemented with attention to both operational metrics and human dimensions, provide feasible pathways toward more resilient, equitable, and efficient warehouse operations. Future research should extend these findings across diverse organisational contexts while deepening investigation into the workforce and sustainability implications, ensuring that technological progress serves broader organisational and societal objectives.

Limitations and Boundary Conditions

Several limitations circumscribe the generalizability of findings:

Temporal limitations: The research encompassed a six-month model development period and four- week forecasting horizon. Longer-term forecasting performance and model stability across extended periods remain unvalidated. Seasonal patterns spanning multiple years could not be fully evaluated within the research timeframe.

Organisational scope: The case study organisation represents a single, centralised distribution warehouse for a multinational retailer for a limited number of products. Generalisation to other warehouse types (e-commerce fulfilment, pharmaceutical distribution, food wholesale) requires validation across diverse operational contexts with different product characteristics, demand patterns, and operational constraints.

Data accessibility: Anonymity requirements and proprietary data concerns precluded access to certain organisational datasets (e.g., detailed product-level demand data, labour cost structures, customer specifications). These limitations constrained certain analytical avenues.

Model assumptions: The simulation model incorporates numerous simplifications regarding employee behaviour, equipment reliability, and demand volatility, reflecting practical constraints on model complexity. While these simplifications remain reasonable for strategic planning, detailed operational analysis might require enhanced model sophistication.

Future Research Directions

This research establishes foundations for extended investigation in several directions:

Temporal extension: Extended validation across multiple years would enable assessment of model performance across diverse seasonal and cyclical patterns, providing confidence in long-term operational planning applications.

Organisational diversity: Replication across warehouses serving different customer types, product categories, and geographic regions would illuminate whether findings reflect general principles or organisational-specific contingencies.

Advanced analytics integration: Incorporating additional data sources (weather, economic indicators, social media sentiment) might enhance forecasting accuracy, particularly for promotional-driven demand patterns.

Equity metrics expansion: Developing comprehensive workforce equity metrics beyond schedule predictability (e.g., compensation equity, distribution of training and development opportunities, health and safety outcomes) would deepen understanding of technology's human implications.

Real-time optimisation: Implementing online learning mechanisms that enable model adaptation to emerging patterns would extend the static forecasting approach toward dynamic, continuously updated predictions.

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Umetna inteligenca za povečanje učinkovitosti skladiščne logistike: študija primera

Izvleček

Prispevek proučuje, kako lahko napovedovanje z umetno inteligenco (UI) in simulacija diskretnih dogodkov podpirata prilagodljivo načrtovanje skladiščnega poslovanja z vključevanjem učinkovitosti, uravnoteženosti delovnih obremenitev in operativne odpornosti. Na podlagi podatkov distribucijskega skladišča z modeli strojnega učenja napovedujemo dnevno pojavnost dobav in količine naročil, z uporabo simulacijskih modelov simuliramo skladiščne procese, prepoznavamo omejitve zmogljivosti ter preverjamo različne scenarije razporejanja zaposlenih in prostorske ureditve. Rezultati kažejo, da napovedna analitika zagotavlja stabilno podlago za kratkoročno načrtovanje, medtem ko simulacija opredeljuje komisioniranje naročil kot glavno operativno ozko grlo in področje z najvišjo izkoriščenostjo virov. Študija prispeva k raziskavam na področju kibernetike in sistemskega mišljenja z operacionalizacijo integriranega načrtovalskega postopka, v katerem napovedne povratne informacije usmerjajo simulacijsko eksperimentiranje in dinamično usklajevanje zmogljivosti. Predlagani okvir združuje pretočnost, izkoriščenost virov, porazdelitev delovnih obremenitev in obremenjenost zaposlenih v enoten pristop prilagodljivega načrtovanja. Prispevek ponuja ponovljiv analitični pristop za raziskovalce ter praktične smernice za vodje, ki si prizadevajo za bolj tekoče delovne procese in trajnostnejšo uporabo virov.

Ključne besede: umetna inteligenca, napovedna analitika, simulacija diskretnih dogodkov, optimizacija skladiščnega poslovanja, napovedovanje povpraševanja, upravljanje operacij