



Integration of Artificial Intelligence into Modular Business Systems: Automating Workload Allocation and Demand Forecasting to Enhance Enterprise Manageability

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Abstract

This article examines the potential applications of artificial intelligence (hereinafter referred to as AI) within modular business systems. Particular attention is given to managerial tasks related to demand forecasting, workload allocation, time-buffer calculation, fulfillment planning, and the analysis of customer inquiries. The aim of the article is to develop an applied model for integrating AI into a modular business system in order to improve planning accuracy and reduce the risk of overloading individual modules. The methodological foundation of the study is based on an analysis of scholarly publications published between 2020 and 2026, as well as modeling and scenario-based evaluation of calculated data. An AI implementation algorithm is proposed, incorporating data auditing, predictive model training, deployment of a recommendation dashboard, and the gradual transfer of selected decision-making functions to an automated allocation module. The findings demonstrate that the use of AI-driven recommendations can reduce planning-related labor costs, improve capacity utilization, and decrease the frequency of missed deadlines. The study concludes that AI strengthens a modular enterprise system through the effective use of data, forecasting capabilities, and decision-making rules.

Keywords: artificial intelligence, modular business system, demand forecasting, workload allocation, supply chain management, business automation

1. Introduction

A modular business system is built upon the division of an enterprise into relatively autonomous functional units, each responsible for its own operations, resources, timelines, and performance outcomes. The modular approach offers significant long-term advantages, as it enables growing enterprises to transform functional departments such as sales, production, warehousing, delivery, service, procurement, customer support, and analytics into manageable units operating as independent profit centers. At the same time, an increase in the number of modules intensifies the requirements for coordination and communication among them. In particular, it becomes essential to understand the current workload of each module, the availability of reserve capacity, and the extent to which additional external orders can be accepted without jeopardizing delivery deadlines. In traditional management systems, planning is often based on manual processes, where managers compare incoming orders, delivery schedules, inventory levels, and other operational data. While such an approach may be adequate at relatively low levels of activity, management delays associated with planning become increasingly common as the enterprise scales and order volumes grow.

In this regard, AI technology enables a shift toward data-driven decision support, in contrast to the traditional reactive approach to management. In the scholarly literature, demand forecasting is regarded as one of the principal areas of application for machine learning and deep learning methods in supply chain management, as these approaches make it possible to account for seasonality effects, historical sales data, external influences, and nonlinear relationships among variables (Douaioui et al., 2024). Within a modular business system, however, the role of AI extends beyond forecasting itself, as demand forecasts serve as the foundation for assessing the future workload of each module.

Studies on AI applications in supply chain management emphasize that artificial intelligence is widely employed for inventory planning, resource allocation, risk management, routing, and decision support under conditions of fluctuating demand (Daios et al., 2025). Accordingly, the integration of AI into a modular business system should primarily be viewed as a managerial challenge associated with transforming data on orders, delivery timelines, inventory levels, disruptions, and customer inquiries into actionable recommendations for decision-making.

The aim of the present article is to develop a model for integrating AI into a modular business system. The proposed model is designed to automate demand forecasting, assess module workloads, calculate time buffers, and generate recommendations regarding the acceptance of external orders. The scientific significance of the study lies in advancing the integration of modular enterprise design with AI-driven planning tools. Its practical significance stems from the possibility of applying the proposed algorithm in service-based, trading, production-service, and fulfillment-oriented companies.

2. Materials and Methods

The research materials consisted of relevant scholarly publications published between 2020 and 2026. Particular attention was given to studies addressing artificial intelligence in supply chain management, demand forecasting, digital twins, production planning, CRM automation, and AI adoption in small and medium-sized enterprises. Sources were selected based on their relevance to modular management, practical applicability, and the potential to use the authors' findings in developing an AI implementation algorithm. The methodological framework of the study combines thematic literature analysis, conceptual modeling, scenario-based evaluation, and quantitative calculations. Thematic analysis made it possible to identify four principal areas of AI application: demand forecasting, workload allocation, fulfillment operations, and customer analytics. Conceptual modeling was employed to describe the relationships among data inputs, forecasting mechanisms, recommendation modules, and managerial decision-making. Scenario-based evaluation was used to compare three enterprise operating models: manual planning, recommendation-dashboard support, and partially automated order allocation. Contemporary reviews of intelligent supply chain management indicate that the greatest managerial benefits of AI are achieved when forecasting, operational monitoring, and decision-support functions are integrated within a unified enterprise information environment (Teixeira et al., 2025). Accordingly, the modular business system is conceptualized in this article as a data flow architecture in which inputs include order history, process durations, failure rates, employee workload levels, inventory balances, delivery performance indicators, customer inquiries, and seasonal coefficients, while outputs consist of recommendations regarding order acceptance, task reallocation, and the adjustment of time buffers. To evaluate performance outcomes, the study proposes a quantitative indicator of modular system manageability:

$$I = 0.30F + 0.25U + 0.25T + 0.20L,$$

where I represents the overall manageability indicator; F denotes demand forecasting accuracy; U refers to the efficiency of capacity utilization; T reflects the reliability of deadline adherence; and L represents managerial labor savings. All indicators are normalized to a scale ranging from 0 to 1. Forecasting accuracy is assigned the highest weight because it determines the quality of subsequent managerial decisions. It should be noted

that the proposed composite indicator is not intended to replace financial performance measures; rather, it is used to compare enterprise performance across scenarios before and after the implementation of AI-driven automation tools.

The transition toward automation in supply chain management is associated with the growing importance of real-time information flows. Researchers emphasize that AI-based tools are particularly effective in situations where information movement and resource allocation decisions must be coordinated within short time horizons (Shamsuddoha et al., 2025). For a modular enterprise, it is therefore advisable to integrate demand-related data with information on the actual readiness of individual modules to fulfill incoming orders. These considerations formed the basis for the study’s main conclusions.

3. Results and Discussion

Artificial intelligence is most effectively implemented as a decision-support mechanism integrated with an enterprise’s operational data. In this context, several key points of implementation can be identified:

1. demand forecasting; for each module, a weekly forecast of incoming tasks is generated. A planning horizon of two to four weeks is sufficient for adjusting schedules, procurement activities, and workforce allocation;
2. time-buffer calculation; in manual planning systems, time reserves are typically assigned uniformly across all orders, which leads to two common problems: some orders receive excessive buffers, while others are left without a realistic reserve. An AI model can calculate time buffers based on execution history, seasonal patterns, customer type, and the current workload of the module;
3. route optimization and warehouse workload management; reviews of logistics optimization demonstrate that AI is widely applied to routing, inventory planning, and the alignment of economic and environmental objectives in goods movement (Chen et al., 2024). Within a modular business system, this functionality is reflected in the selection of warehouse locations, order-picking priorities, and delivery routes;
4. call center and CRM analytics; chatbots and customer inquiry analytics tools make it possible to identify recurring issues, assess shifts in demand based on customer requests, and reduce operator workload. Within a modular system, customer analytics provides signals to sales, service, and warehouse modules, enabling resources to be prepared in advance for anticipated demand.

The identified AI integration points within a modular business system are summarized in Table 1:

Table 1. AI integration points in a modular business system

Integration point	Input data	AI tool	Management decision	Expected effect
Demand forecasting	Sales history, seasonality, external orders	ML/DL forecast model	Accept, postpone or reject an order	Lower overload risk
Time buffer planning	Operation duration, delays, failures	Predictive buffer model	Set reserve time for each order type	Fewer missed deadlines
Fulfillment planning	Warehouse load, stock, routes	Optimization model	Select warehouse and delivery route	Higher capacity use
CRM and call center	Requests, complaints, repeat questions	Chatbot and text analytics	Redirect client issues and update demand signals	Lower service cost
Workload allocation	Module capacity, staff schedule, order priority	Recommendation dashboard	Redistribute tasks among modules	Better resource use

However, for implementation to be effective, it is advisable to follow a structured AI adoption algorithm. The process should begin with a data audit, during which the organization identifies which data are already

captured within its information systems, which indicators are still maintained manually, where data gaps exist, and which modules possess reliable historical records. It is important to emphasize that a model cannot be effectively trained on data that do not accurately reflect actual operational conditions. Therefore, the primary task is the cleansing and alignment of data related to orders, delivery timelines, failures, workload levels, and customer inquiries.

The next important stage involves the development of a feature set for the AI model. Demand forecasting typically relies on variables such as the week of the year, customer type, order acquisition channel, average order value, product category, historical cancellations, inventory levels, and external factors. For workload forecasting, additional variables include process duration, workforce availability, equipment availability, and the number of concurrent orders. In production planning, digital twins and AI technologies make it possible to analyze operational schedules, queue dynamics, and resource availability, making this approach particularly valuable for modular enterprises characterized by repetitive processes (Singh et al., 2026).

The next stage involves training a forecasting model with a planning horizon of two to four weeks, during which several alternative models are evaluated and compared. For small enterprises, gradient boosting models, random forests, or LSTM models are generally sufficient when a long historical time series is available. For enterprises operating with a large number of modules, a multi-agent architecture may be employed, in which each module is represented by an independent agent. Studies on deep reinforcement learning in the Industrial Internet of Things highlight the applicability and potential of multi-agent approaches for resource allocation across interconnected system nodes (Rosenberger et al., 2022). The subsequent stage involves the deployment of a recommendation dashboard that displays projected module workloads, overload risks, available capacity, forecasts of potential deadline violations, and recommendations regarding external orders. Decision-making authority remains with managers, which helps mitigate employee resistance to technological change while simultaneously enabling the evaluation of forecasting quality under real operating conditions.

The fifth stage is associated with partial automation of task allocation. Following validation of the forecasting model, selected routine decisions can be delegated to an AI module. For example, the system may automatically assign a warehouse, generate an order-picking sequence, or recommend the rescheduling of an order. Research on dispatching rules demonstrates that deep reinforcement learning can be applied to the selection of dispatching policies in manufacturing systems (Alexopoulos et al., 2025). Within a business system, this implies the ability to select allocation rules based on actual workload conditions and order urgency.

Collectively, the proposed algorithm can be represented as follows (Figure 1):

Algorithm for Implementing AI in the Enterprise's Modular Business System

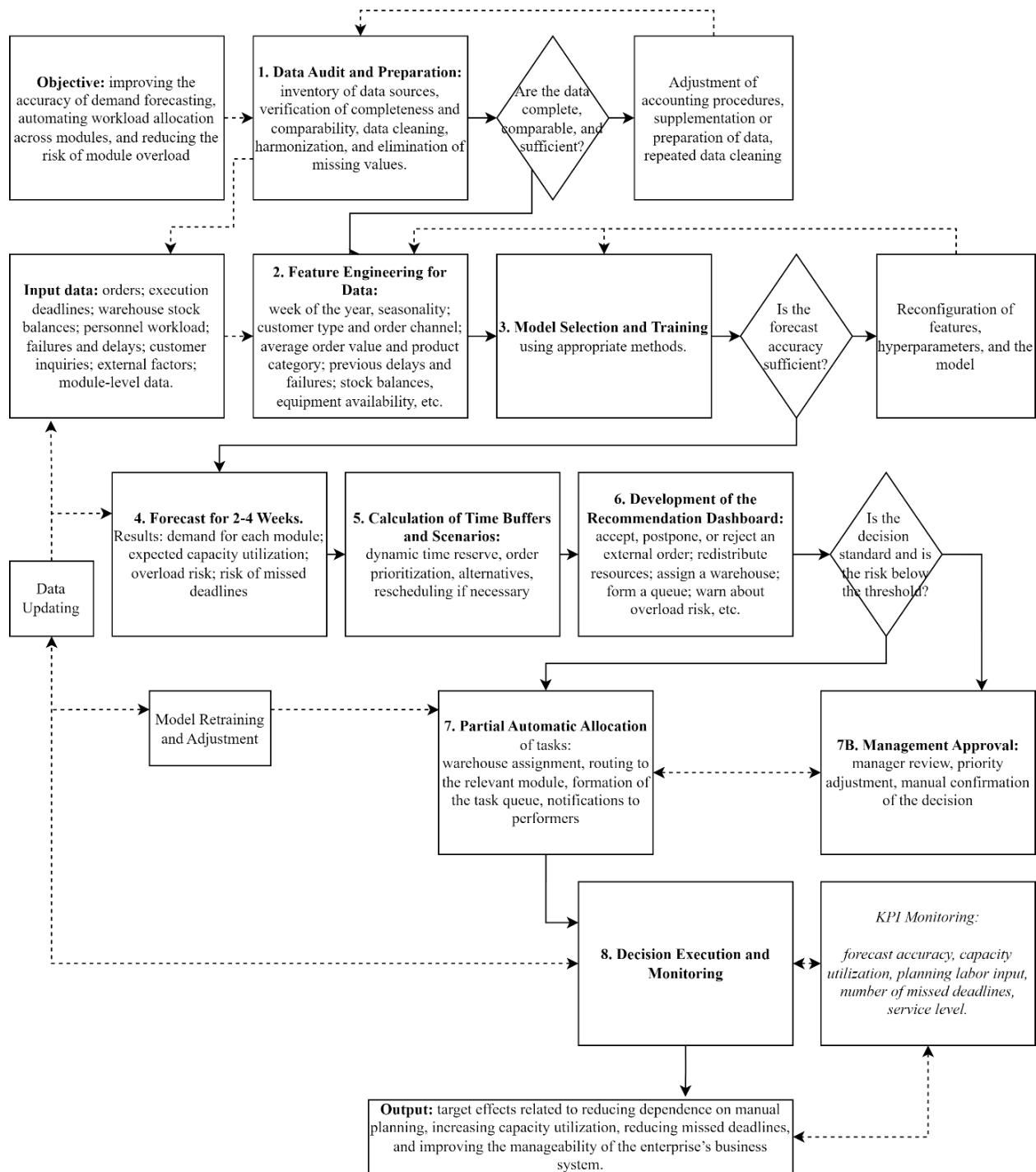


Figure 1. AI integration model for a modular business system

Equally important in the context of applying the proposed algorithm is the issue of workload allocation within a modular business system. Workload allocation in a modular environment should account for three key parameters: expected demand, available capacity, and the risk of deadline violations. When an order is received during a period of high utilization, the system must evaluate both the current and projected workload of the module over the coming weeks. In practice, this approach helps prevent situations in which an order is

accepted due to the availability of capacity at the present moment but subsequently creates overload conditions at the time of execution.

A digital twin may be employed as a computational replica of an enterprise’s processes and incorporated into the workflow between incoming data and subsequent decision-making stages. Reviews of AI-based digital twin applications demonstrate that digital twins are used to integrate data related to operators, products, and processes, thereby enabling the monitoring of operational conditions and the prediction of decision outcomes (Alfaro-Viquez et al., 2025). Within a modular business system, this approach is particularly applicable to the allocation of external orders. For example, if a new order increases warehouse utilization to a critical level, the system should propose an alternative solution, such as rescheduling the delivery date, assigning a different warehouse, engaging temporary personnel, or declining the order. At the same time, supply chain stability also depends on an enterprise’s ability to rapidly assess the consequences of external disruptions. Studies on digital twins in supply chain resilience indicate that digital twins facilitate the modeling of supply interruptions, delivery delays, and changes in resource availability (Roman et al., 2025). Accordingly, within a modular business system, AI should operate under both normal and stress conditions. The normal mode supports the planning of current demand, whereas the stress mode identifies which modules are likely to become bottlenecks first in the event of a demand surge or supply delay.

Thus, in order to evaluate the effect of the proposed approach, a simulation was conducted using a model enterprise consisting of five modules: sales, warehousing, fulfillment, delivery, and customer service. Three scenarios were compared:

1. corresponded to manual planning;
2. involved the use of an AI dashboard that provided recommendations to managers;
3. incorporated partial automation of routine order allocation.

The challenge of AI implementation in small and medium-sized enterprises is associated with limitations in data availability, expertise, and financial resources. Research on AI adoption in SMEs based on the TOE-DOI framework indicates that implementation outcomes depend on technological readiness, organizational conditions, and employees’ perceptions of innovation (Sánchez et al., 2025). Therefore, the assessment conducted in this study does not assume an immediate transition to full automation. Instead, the most realistic approach is an intermediate operating mode based on a recommendation dashboard.

Table 2. Modeled effects of AI implementation in a modular business system

Indicator	Manual planning	AI recommendations	Partial auto-matic allocation
Forecast accuracy, %	68	82	88
Capacity utilization, %	71	82	88
Planner labor input, hours/month	42	22	13
Missed deadlines, cases/month	14	8	5
Orders accepted with overload risk, cases/month	18	11	7
Management score I	0.61	0.78	0.87

According to the data presented in the example, the transition from manual planning to AI-driven recommendations reduces planners’ workload from 42 to 22 hours per month, representing a 48% reduction. When partial automated allocation is introduced, planning effort decreases further to 13 hours per month, corresponding to a 69% reduction relative to the baseline scenario. Capacity utilization increases from 71% to 88%, representing a 17% improvement, while the number of missed deadlines declines from 14 to 5 cases per month (see Figure 2).

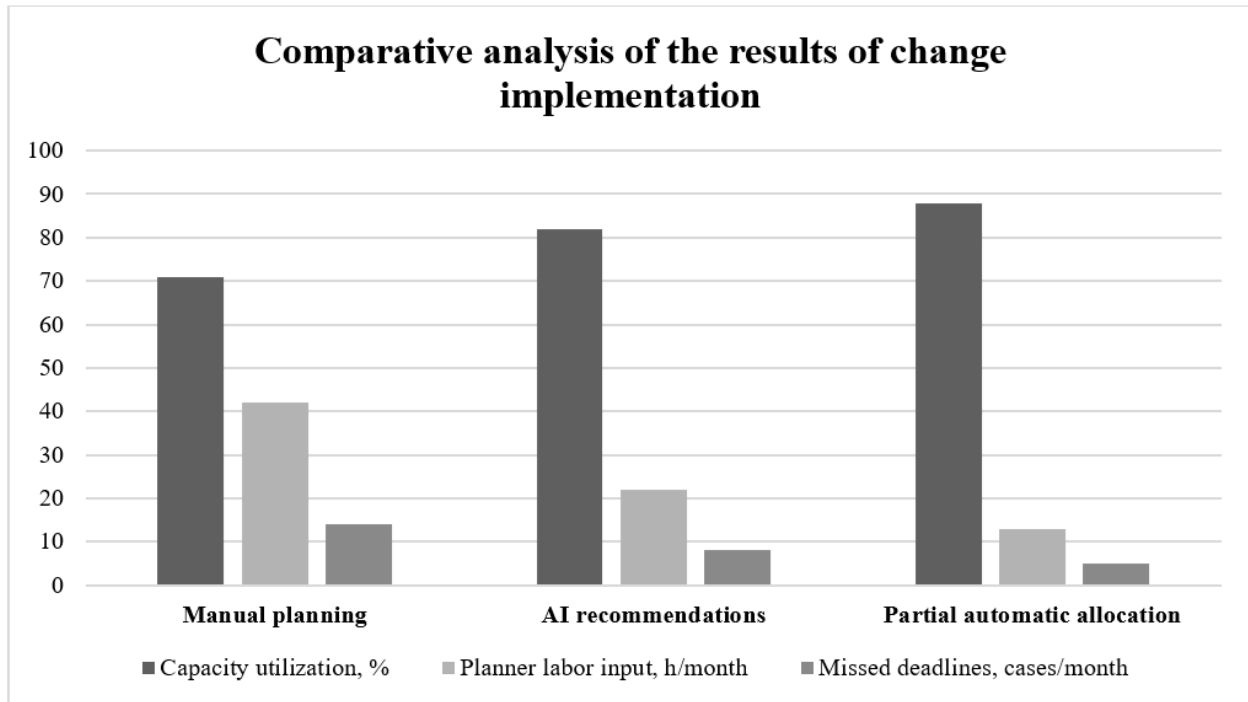


Figure 2. Comparative analysis of the results of change implementation

The calculated results indicate that the primary effect is generated through improvements in the quality of the information available for managerial decision-making. In practice, managers receive a demand forecast, a risk assessment, and a recommended course of action, which enable them to make more informed and well-founded decisions while relying on their professional expertise. Moreover, as historical data accumulate, the system can gradually assume responsibility for repetitive low-risk decisions, thereby reducing the overall managerial workload and increasing order-processing speed over time.

AI also changes the nature of an enterprise’s business model. For example, studies examining the role of AI in business model innovation demonstrate that AI influences value propositions, operational processes, and revenue-generation mechanisms within digital platform companies (Zhang et al., 2025). In a modular business system, this influence is reflected in the ability to provide customers with more accurate delivery timelines, accept a greater number of external orders without creating overload conditions, and respond more rapidly to changes in demand. For small and medium-sized enterprises, however, the financial effects of AI implementation should be evaluated with greater caution. For instance, research on AI-driven business model innovation in South Asian SMEs indicates that the outcomes of AI adoption vary according to firms’ levels of readiness and depend on managerial conditions, industry characteristics, and data quality (Rahman, 2025). Therefore, the economic effects identified in this study require further investigation and validation in future research.

In addition, it is important to recognize that the integration of AI into a modular business system requires compliance with several key conditions:

1. a unified data structure, since each module must record operations in a comparable format. If the sales department uses one order classification system, the warehouse another, and the service department a third, the forecasting model will generate inconsistent recommendations;
2. formalized governance procedures, as it is necessary to determine in advance which decisions are recommended by AI and which may be executed automatically. For example, the system may recommend

rejecting an order, while the final decision remains with the manager. At the same time, warehouse assignment or time-buffer calculation may be performed automatically without additional approval if the associated risk remains below a predefined threshold;

3. legally and ethically compliant data management, as supported by studies on AI integration in service innovation and business development, which demonstrate that the development of AI-enabled services should be accompanied by compliance with legal requirements, data-processing standards, and managerial oversight (Li et al., 2024). This consideration is particularly important for functional units such as call centers and CRM departments, since customer inquiries often contain personal and sensitive information;
4. participation of partners and employees. Data-driven business model innovation depends on data alignment among business stakeholders and the responsible use of information (Heikkilä et al., 2025). At a minimum, a modular enterprise should clearly communicate the purpose of the AI dashboard to employees. The system should not be perceived as a tool for penalizing low utilization or delays, as its primary purpose is to improve planning accuracy;
5. customer analytics, based on the premise that AI enables faster processing of customer signals and more effective adjustment of marketing activities (Stancu & Panait, 2025). Within a modular business system, these signals are important for demand forecasting, allowing the system to provide advance warnings to sales, warehouse, and service modules;
6. organizational learning. According to recent research, the benefits of AI are amplified when organizations develop the capability to learn from data and revise operational procedures accordingly (Han et al., 2025). Therefore, AI implementation should be accompanied by managerial training, the adjustment of performance metrics, and the regular review of forecasting errors.

At the same time, AI applications may also support transformative managerial change. For example, studies have identified a relationship between the use of AI and sustainable breakthrough innovation when the technology is embedded within managerial processes and applied to decisions that influence a company's long-term development (Sun et al., 2025). Within a modular business system, such outcomes can be achieved through the integrated use of forecasting, resource allocation, and execution monitoring.

The role of CRM within the overall system also deserves particular attention, as customer support represents an important module in workload allocation. Customer inquiries often precede changes in demand; therefore, if clients begin asking large numbers of questions regarding delivery timelines, product availability, shipment status, or new services, these signals can be incorporated into forecasting models. Chatbots make it possible to reduce operator workload while simultaneously collecting data on recurring customer requests, a benefit confirmed by contemporary research. Studies have demonstrated that chatbots generate both economic and managerial benefits through lower operating costs, faster inquiry processing, and enhanced customer experience (Khneyzer et al., 2024). For small enterprises, chatbot implementation may serve as the first step toward a fully developed AI-driven system. Moreover, even limited chatbot adoption can alter the distribution of customer inquiries, improve response times, and provide business owners with valuable data for managerial decision-making (Marcineková et al., 2025). Within a modular business system, such data are transmitted to the forecasting component, enabling more accurate estimation of future workloads in sales, warehousing, and service operations.

4. Conclusions

The article proposes an algorithm for integrating AI into a modular business system. The central idea is the use of AI as a decision-support mechanism for demand forecasting, workload management, deadline planning, and the acceptance of external orders. In this capacity, AI connects enterprise modules through data, forecasts, and task-allocation rules. Four principal areas of implementation were identified: demand forecasting, time-buffer calculation, fulfillment operations, and customer analytics. For each area, the corresponding input data, AI tool, managerial decision, and expected effect were specified. The proposed implementation algorithm begins with a data audit and concludes with the partial automation of routine decisions, thereby reducing the risk of implementation errors and enabling personnel to gradually transition toward working with AI-generated recommendations. The scenario-based evaluation demonstrated that the use of an AI dashboard combined with partial automated allocation can improve forecasting accuracy, enhance capacity utilization, and reduce the number of missed deadlines, which is consistent with the existing evidence on the practical application of AI.

The practical value of the proposed approach lies in its potential to serve as a foundation for pilot AI implementation. Following the proposed algorithm, an enterprise first collects data across its modules, then trains a forecasting model, deploys a recommendation dashboard, and gradually transfers routine decisions to the system. Future research may focus on the empirical validation of the model using extensive datasets obtained from actual enterprises. Another promising direction involves comparing industries in which modular organizational structures exert different levels of influence on operational and business performance outcomes.

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