

ARTIFICIAL INTELLIGENCE AND DIGITAL TRANSFORMATION IN COMMERCE: APPLICATIONS IN DEMAND FORECASTING AND INVENTORY MANAGEMENT

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Abstract

Artificial intelligence (AI) is becoming an important component of digital transformation in commerce, particularly in activities that depend on the timely interpretation of large and changing datasets. Among these, demand forecasting and inventory management directly influence purchasing, warehousing, distribution and customer service. This paper examines how AI-supported forecasting can connect historical sales, customer behaviour, prices, promotions, seasonal effects and selected external factors with inventory decisions. Using a narrative review of concepts and applications supported by selected peer-reviewed literature on AI and supply chain management, it discusses machine learning, deep learning, time-series analysis and predictive analytics as tools for identifying demand patterns and supporting replenishment decisions. The review indicates that AI can strengthen planning by processing multiple variables at speed, identifying relationships that are difficult to detect manually and supporting more responsive inventory decisions, but it does not remove the need for managerial judgement. Forecast quality depends on the quality and relevance of data, and implementation can be constrained by cost, cybersecurity requirements, skills gaps, system integration and unexpected changes in customer behaviour. The paper therefore presents AI-enabled demand forecasting as a decision-support capability rather than a fully autonomous replacement for commercial management and proposes an implementation framework in which data preparation, forecasting, inventory planning, monitoring and continuous improvement are connected stages. It concludes that the value of AI in commerce depends not only on the forecasting technique selected but also on the quality of business processes, human oversight and responsible data management.

Keywords

Artificial Intelligence, Digital Transformation, Commerce, Demand Forecasting, Inventory Management, Supply Chain, Machine Learning, Predictive Analytics

1. Introduction

Digital transformation has changed the way commercial organisations collect information, communicate with customers, manage transactions and coordinate supply activities. Retailers, distributors and online businesses now generate data from sales transactions, customer interactions, digital payments, warehouse systems, promotions and online activity. The challenge is no longer simply obtaining information but converting it into decisions quickly enough to respond to changing demand.

AI provides one route for addressing this challenge. In supply chain management, AI has been studied across demand forecasting, inventory management, logistics, production, marketing and supplier-related decisions. A systematic literature review by Toorajipour et al. (2021) shows that AI applications have expanded across several supply chain fields, while more recent reviews continue to identify demand forecasting and inventory management as major application areas (“Artificial Intelligence in Supply Chain Management,” 2024;

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“Examining the Integration,” 2024). These findings place AI within a broader shift towards data-driven supply chain planning rather than treating it as a stand-alone technology.

Demand forecasting is particularly important because inventory decisions are made before actual customer demand is known. If demand is underestimated, products may become unavailable and sales may be lost; if it is overestimated, capital can remain tied up in slow-moving stock and storage or waste costs can increase. This paper therefore focuses on the practical relationship between AI-based demand forecasting and inventory management, explaining the data required for forecasting, the main analytical techniques, the process through which forecasts are converted into inventory decisions, the potential benefits and limitations, and the conditions required for responsible implementation.

2. Review Approach

The paper uses a narrative literature-review approach. The concepts and applications of AI in demand forecasting and inventory management were organised into a structured discussion and supported by selected peer-reviewed publications on AI in supply chain management, predictive analytics and demand planning. No primary survey, experiment, company dataset or original forecasting model was used; the paper therefore does not claim empirical measurement of forecasting accuracy or financial performance, and its conclusions should be interpreted as a conceptual synthesis of the reviewed literature.

3. AI and Digital Transformation in Commerce

AI refers to computational methods that enable systems to perform tasks such as pattern recognition, prediction, classification and decision support. In commerce, these capabilities can be applied to customer service, marketing, fraud detection, sales analysis, logistics and supply planning, and digital transformation provides the wider environment in which they operate by connecting data, software, communication systems and business processes.

The commercial value of AI is therefore linked to integration. A forecasting model operating on isolated or unreliable data may produce outputs that are difficult to use, whereas when sales, inventory, customer, pricing, promotion and supply information are connected, AI can become part of a continuous planning process. Research on predictive analytics in supply chain management has similarly emphasised combining quantitative methods with supply chain knowledge rather than treating analytics as an independent technical activity (Waller & Fawcett, 2013).

4. Demand Forecasting as a Commercial Decision Process

Demand forecasting is the estimation of future demand for a product or service over a specified period. Forecasts may be required for individual products, stores, customer groups, product categories or broader markets, depending on the decision being supported: procurement may require product-level forecasts, while strategic planning may use aggregated category-level information. Traditional forecasting relies heavily on historical sales and managerial judgement, which remain useful, but demand is also influenced by seasonality, price changes, promotions, competitor activity, special events, weather and changing customer preferences. AI-based forecasting can combine several of these variables and search for relationships within larger datasets (“Review and Analysis,” 2022). The main data inputs are as follows:

- Historical sales: evidence of previous purchasing patterns and recurring demand.
- Customer information: purchasing behaviour and differences between customer groups.
- Seasonal and event information: changes associated with holidays, festivals, school periods or other recurring events.
- Price and promotion data: the effects of price changes, discounts and promotional campaigns.
- Market and external information: competitor activity, weather, economic conditions, search activity or other market-specific variables.

5. AI Techniques Used in Demand

Forecasting

Machine learning: Machine-learning methods identify patterns in historical observations and use them to generate predictions. In demand planning, they can incorporate multiple explanatory variables rather than relying on a single historical series, which is useful when demand is influenced by several interacting factors. Machine-learning applications in supply chain management have grown substantially, with demand forecasting among the most frequently studied applications (“On the Use of Machine Learning,” 2025).

Deep learning: Deep learning uses multi-layer neural-network architectures and can be applied to large and complex datasets, with potential value in modelling nonlinear relationships and high-dimensional patterns. However, greater model complexity does not automatically guarantee better business decisions; data availability, model validation, interpretability, computing requirements and the specific forecasting problem must be considered before adoption.

Time-series analysis: Time-series analysis examines observations over time to identify trend, seasonality and changes in demand. Such methods remain important because many commercial decisions are inherently temporal, and AI methods can

complement them when additional variables or more complex relationships need to be considered.

Predictive analytics: Predictive analytics uses historical and current information to estimate possible future outcomes and can support demand planning, inventory decisions and logistics planning (Waller & Fawcett, 2013). The important distinction is that a prediction is an input to a decision, not the decision itself.

6. From Forecast to Inventory Decision

Forecasting becomes commercially useful when its output is connected to inventory planning, which involves deciding how much stock to order, when to reorder, where stock should be positioned and how to respond when actual demand differs from the forecast. The operating cycle shown in Figure 1 has seven stages: the organisation collects relevant sales, customer, inventory, price, promotion and market information; the data are cleaned, structured and checked for missing or inconsistent records; the forecasting model analyses the prepared data; the system generates a demand estimate; planners translate the estimate into purchasing and inventory actions; actual sales and inventory movements are monitored; and forecast performance is reviewed and the process adjusted using new information.



Figure 1. AI-Enabled Forecast-to-Delivery Cycle

Inventory imbalance: Two broad inventory problems illustrate why forecasting matters. Excess inventory increases storage requirements, ties up working capital and creates a risk of obsolescence or expiry, while insufficient inventory leads to stock-outs, delayed fulfilment, lost sales and customer dissatisfaction. AI does not eliminate these risks, but better information and more responsive forecasting can help planners recognise changing demand earlier.

7. Applications Across the Supply Chain

AI-enabled forecasting can influence more than the purchasing decision. At the supplier stage, demand information supports order planning; at the warehouse stage, expected demand influences stock allocation and replenishment; at the distribution stage, forecasts help planners anticipate delivery requirements and transport capacity; and at the retail stage, expected demand informs shelf availability and promotional planning. Logistics is closely connected to these decisions: AI-supported systems can assist with delivery planning, shipment monitoring, route optimisation and the identification of possible delays, so that inventory and movement decisions are coordinated rather than managed separately (Toorajipour et al., 2021).

8. Potential Benefits for Commerce

- Improved planning: forecasts provide an evidence-based input for purchasing, replenishment and distribution decisions.
- Lower risk of stock-outs: earlier identification of demand increases helps businesses prepare inventory before shortages occur.
- Reduced excess inventory: more responsive planning reduces unnecessary purchasing and the associated storage burden.
- Better use of resources: inventory space, working capital, labour and transport capacity can be planned with greater visibility.
- Improved customer service: better product availability and fulfilment planning contribute to a more consistent customer experience.

- Faster analysis: AI systems process large datasets more rapidly than manual analysis, allowing more frequent review.

- Waste reduction: for products with limited shelf life, closer alignment between expected demand and purchasing reduces the risk of unsold or expired stock.

9. Challenges and Limitations

- Data quality: incomplete, inconsistent, outdated or incorrectly recorded data reduce the usefulness of a forecasting model.

- Implementation cost: adoption may require investment in software, infrastructure, integration, data preparation and skilled personnel.

- Skills and training: employees need sufficient understanding of both the business process and the analytical system to interpret forecasts appropriately.

- Cybersecurity and privacy: commercial and customer data must be protected from unauthorised access and inappropriate use.

- Changing behaviour: sudden shifts in customer preferences, unexpected events or market disruptions can reduce the relevance of historical patterns.

- System dependence: forecasting can be affected by system outages, poor integration or a lack of technical support.

- Interpretability and governance: managers may need to understand why a model produces a particular forecast, especially when it affects high-value inventory or customer commitments.

These limitations show why AI should be treated as part of an organisational capability rather than a plug-in solution. Recent reviews identify data integration, organisational adoption, skills and implementation conditions as continuing issues alongside the technical development of AI methods (“Application of Artificial Intelligence in Demand Planning,” 2025; “Artificial Intelligence in Supply Chain Management,” 2024).

10. Proposed Implementation

Framework

A practical AI-enabled forecasting programme can be organised around five connected capabilities,

which consolidate the process described above with themes identified in the reviewed literature (Table 1).

Table 1. Proposed Implementation Framework for AI-Enabled Demand Forecasting

Stage	Main activity	Management focus
1. Data foundation	Collect, clean, integrate and validate relevant data.	Accuracy, completeness, access and governance.
2. Forecast development	Select and validate an appropriate statistical or AI method.	Forecast error, business context and interpretability.
3. Inventory translation	Convert forecasts into reorder, allocation and purchasing decisions.	Service level, stock exposure, lead time and working capital.
4. Operational monitoring	Compare actual demand with forecasts and track inventory outcomes.	Exceptions, deviations and operational response.
5. Continuous improvement	Update data, review model performance and incorporate managerial learning.	Adaptation, accountability and sustained performance.

Source: Developed by the authors

The framework deliberately places human review within the process. A forecast can identify a likely increase in demand, but a manager may still need to consider supplier lead time, available cash, warehouse capacity, minimum order quantities, promotional plans or unusual market information; human judgement is therefore complementary to model output.

Illustrative example: Consider an online clothing retailer preparing for a festival period. Historical transactions show that selected products experienced higher demand during comparable periods, and the retailer combines this information with current sales, search activity, pricing, promotions and inventory records. An AI-supported forecasting system identifies a probable increase in demand for selected products, and the forecast is used to review purchase quantities, supplier communication, warehouse allocation and delivery capacity. As the festival approaches, actual sales are compared with the forecast and the replenishment plan is adjusted if demand differs materially. The value of the system thus depends not only on the initial prediction but also on the organisation's ability to monitor results and act on new information.

11. Future Scope

Future development is likely to focus on more

connected and responsive planning environments. Cloud computing, Internet of Things (IoT) devices, automation and data analytics can provide additional real-time information for supply chain decisions, supporting more frequent inventory updates, automated replenishment alerts, improved warehouse visibility and faster response to changes in demand. Future research should move beyond claims of general improvement and examine where particular AI methods work well, under what data conditions they fail and how managers use model outputs in practice; comparisons across product categories, demand patterns, forecast horizons and business sizes would help establish more precise guidance for commercial adoption.

12. Conclusion

AI has an expanding role in the digital transformation of commerce, and demand forecasting provides a clear example of how analytical technologies influence everyday business decisions. By combining historical sales with customer, price, promotion, seasonal and selected external information, AI-supported systems provide a richer basis for estimating future demand, and better anticipation of demand can support purchasing, replenishment, stock allocation, logistics and customer service while reducing avoidable overstock or stock-

outs. These benefits are not automatic outcomes of adopting AI, however: forecast quality depends on data, model selection, implementation, monitoring and the ability of employees to interpret and act on the results.

The central implication of this review is that AI should be implemented as a decision-support capability embedded within sound commercial processes. Organisations that combine reliable data, appropriate forecasting methods, human oversight, employee capability and responsible data governance are better positioned to use AI as part of continuous digital transformation. Further empirical research is needed to measure the effect of specific AI forecasting approaches across different commerce contexts.

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