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A multi-level AI-driven product policy model for retail chains as a conceptual framework for marketing consulting

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Abstract. The rapid development of omnichannel distribution systems and the increasing need to improve the speed and accuracy of marketing decision-making in product policy create a strong demand for the implementation of algorithmic data analysis methods and artificial intelligence technologies. This study aimed to develop the theoretical and methodological foundations of product policy management in retail enterprises through the design of a conceptual multi-level AI-driven product policy model. The research was based on a combination of general scientific and specialised methods, including analysis and synthesis, comparative analysis, systems analysis, structural-logical modelling, abstraction, and generalisation. The proposed model was conceptualised as an adaptive self-regulating system that integrates data, machine learning algorithms, and managerial decision-making processes and serves as a methodological platform for marketing consulting aimed at implementing intelligence-supported decisions in retail practice. The study provided a theoretical justification for the transition toward AI-driven product policy by identifying the system-forming role of data in marketing decision-making, analysing the capabilities of machine learning algorithms, and specifying directions for their application in demand forecasting, assortment optimisation, and automated inventory management. As a result, a conceptual multi-level model of AI-driven product policy was developed, integrating data infrastructure, machine learning analytics, managerial decision-making, and marketing consulting support into a unified adaptive management cycle. The model functions as an integrated closed-loop system with a feedback mechanism and includes the stages of data collection and integration, algorithmic forecasting and AI-based analytics, managerial decision-making for assortment optimisation and automated inventory management, and KPI-based performance monitoring. The practical significance of the research lies in the possibility of applying the proposed model as a methodological tool for marketing consulting aimed at increasing the adaptability of retail enterprises, reducing operational costs, accelerating inventory turnover, and strengthening competitive positions through data-driven management

Keywords: marketing decision-making; marketing planning; data-driven management; digital analytics; product portfolio; market-product strategy; omnichannel retail

Introduction

In the condition of the digital economy, data increasingly acquire the status of a strategic asset that determines the competitiveness of enterprises in the marketplace, forms the foundation for managerial decision-making, and facilitates the transition toward intelligent models of business processes. The systematic use of data creates the preconditions for the implementation of algorithmic analytics, forecasting of market dynamics, and improvement of the

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adaptability of management systems. From this perspective, the integration of data, machine learning technologies, and marketing instruments becomes a key driver in the transformation of product policy in retail enterprises and forms the methodological basis for the development of marketing consulting as a mechanism for implementing intelligence-supported managerial decisions. Against this backdrop, the role of data in shaping effective product policy becomes particularly significant, as it directly influences the quality of managerial decisions and the ability of enterprises to respond to dynamic market changes.

M. Karim (2025) emphasised that product policy, as a central element of a company's marketing activity, largely depends on the quality and completeness of information concerning consumer behaviour, demand dynamics, the competitive environment, and inventory conditions. In this context, M. Naumenko (2024) highlighted that the transition from intuitive approaches to product portfolio management toward evidence-based strategies represents a global trend driven by the increasing availability of digital data and the rapid development of analytical tools for their processing. Within the Ukrainian scientific discourse, considerable attention is paid to issues related to assortment policy management and product portfolio optimisation. In particular, N. Kubyshyna (2019) stressed that assortments should be formed based on the demand of target segments, economic efficiency, and alignment of product offerings with market trends. Similarly, A. Kostromin (2021) examined the role of product policy in ensuring competitiveness and shaping the structure of product lines and demonstrates that effective assortment formation depends on a combination of market demand factors and internal efficiency indicators.

Another research direction is associated with the automation of retail processes and the use of data analytics in trade. In this context Yu. Lytiuha & D. Kotyk (2024) indicated that the implementation of modern analytical and BI systems enables sales analysis, inventory management, and forecasting of replenishment needs, thereby creating the prerequisites for enterprises to transition toward fully data-driven decision-making models. At the same time, Ukrainian studies rarely address the deeper aspects of applying artificial intelligence in product policy. Despite the rapid development of the IT sector and analytical infrastructure in Ukraine, scientific contributions in this area remain fragmented. Issues that require further investigation include the application of machine learning for demand forecasting, Stock Keeping Unit (SKU) optimisation using clustering algorithms, integration of AI with Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) systems, and the modelling of assortments in omnichannel environments.

Researchers are also actively developing conceptual models for implementing AI in retail. S. Sahubar *et al*. (2025) proposed a structured model for integrating intelligent forecasting systems into inventory management processes, emphasising the importance of organisational cultural readiness for digital transformation. R. Fildes *et al*. (2019) argued that traditional demand forecasting methods, which rely primarily on statistical time-series analysis, demonstrate limited accuracy under conditions of high market volatility. Further developing this view, M. Muth *et al*. (2025) showed that changes in consumer behavior, seasonal fluctuations, promotional activity, external shocks such as pandemics, wars, and logistics crises, as well as the acceleration of innovation cycles in the retail and Fast-Moving Consumer Goods (FMCG) sectors, significantly reduce the predictability of demand. In this regard, the authors emphasised the growing need for machine learning algorithms capable of processing large volumes of data, identifying complex nonlinear relationships, and updating predictive models in real time.

At the same time, S. Ankam (2025) argued that traditional demand forecasting methods, which relied primarily on statistical time-series analysis, are increasingly proving insufficiently accurate under conditions of high market volatility. Extending this argument, Y. Yu *et al*. (2024) and A. Zulfia *et al*. (2025) demonstrated that changes in consumer behaviour, seasonal fluctuations, promotional activity, external shocks such as pandemics, wars, and logistics crises, as well as the acceleration of innovation cycles, significantly reduce the predictability of demand. Models such as Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) effectively account for seasonality, promotional activities, weather conditions, behavioural patterns, and other factors that significantly influence demand. In this regard, I. Tarallo *et al*. (2019) pointed out the necessity of applying machine learning algorithms capable of processing large volumes of data, identifying complex nonlinear relationships, and updating predictive models in real time. Another important challenge addressed in the literature is the problem of excessive assortment and declining efficiency of product portfolios.

Overall, international research provides a well-developed theoretical and practical foundation for implementing AI in product policy, whereas Ukrainian studies remain largely focused on traditional approaches to assortment management. The limited number of comprehensive studies addressing the integration of product policy and artificial intelligence creates a need for further research aimed at adapting global approaches to the realities of the Ukrainian retail sector. The purpose of this study was to develop the theoretical and methodological foundations of product policy management in retail enterprises through the design of a conceptual multi-level model of AI-driven product policy functioning as an adaptive self-regulating system that integrates data, machine learning algorithms, and managerial decision-making processes.

Materials and Methods

The methodological basis of this study was a combination of general scientific and specialised research methods. In particular, the methods of analysis and synthesis were applied to generalise theoretical approaches to product policy management and to systematise the directions of artificial intelligence application in retail. The comparative analysis method was used to compare traditional statistical demand forecasting approaches with machine learning algorithms described in international studies. It was conducted based on a set of criteria, including forecasting accuracy, the ability to capture nonlinear relationships (nonlinearity), adaptability to dynamic and volatile market conditions (volatility adaptation), seasonality handling, scalability for large retail datasets, the capacity for real-time model updating and key empirical evidence. These criteria were selected due to their relevance to the specific characteristics of retail environments, particularly in the context of high demand variability and increasing complexity of consumer behaviour. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are the most widely used error metrics in demand forecasting. RMSE emphasises large deviations due to squaring errors, MAE provides a robust measure of average absolute error, and MAPE expresses forecasting accuracy in percentage terms, making it particularly useful for managerial interpretation and comparison across different datasets (Hyndman & Athanasopoulos, 2021).

For the purpose of comparative analysis, a set of representative forecasting models from different methodological groups was selected, including traditional statistical approaches, machine learning algorithms, and deep learning techniques. In particular, the models analysed comprise Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) as baseline statistical methods, Random Forest, Gradient Boosting, and XGBoost as advanced machine learning models, as well as Long Short-Term Memory (LSTM) networks representing deep learning approaches. Additionally, a hybrid model combining XGBoost and LSTM was included in the comparison to capture both nonlinear relationships and temporal dependencies more effectively. The selection of these models reflects their widespread application in retail demand forecasting and their proven ability to address different aspects of data complexity, including large-scale datasets, nonlinear patterns, and dynamic market environments.

A systems approach enabled the interpretation of product policy as a multi-level integrated system combining data, algorithms, and managerial decision-making processes. Such an interpretation also allowed product policy to be considered as a methodological foundation for marketing consulting in the context of digital transformation. The method of structural and logical modeling was applied to develop a conceptual multi-level model of AI-driven product policy as a tool for marketing consulting aimed at implementing intelligence-supported managerial decisions. The development of the conceptual model was carried out through several sequential stages, beginning with the identification of key elements of product policy, followed by the systematisation of data flows, analytical processes, and decision-making mechanisms. Subsequently, these elements were grouped into four interconnected levels, namely data integration, machine learning analytics, managerial decision-making, and performance monitoring. The next stage involved defining the relationships between these levels and establishing feedback mechanisms to ensure system adaptability. Finally, marketing consulting functions were integrated as an interpretative and strategic component of the model. The criteria for structuring the model included functional differentiation of processes, logical sequence of decision-making stages, and their contribution to value creation in retail operations. In addition, the methods of abstraction and generalisation were employed to formulate the theoretical justification of the proposed model and to systematise its key conceptual provisions.

The information base of the research consists of scientific publications by Ukrainian and international scholars addressing issues related to product policy management, the application of business analytics and digital tools in trade, as well as contemporary international studies in the fields of demand forecasting, machine learning, and assortment optimisation. The literature review was conducted using international scientific databases, including Scopus, and Google Scholar. The selection of sources focused primarily on publications from 2020 to 2026 to ensure the relevance of the analysis, while earlier foundational studies were included where necessary. The selection criteria included scientific relevance, methodological rigor, citation frequency, and direct relation to the research topic. The study also relied on analytical materials and practical insights from RELEX Solutions (Kaleva & Småros, n.d.), Increff, Leafio, FieldAssist, and Optiply, whose platforms illustrate the practical implementation of AI-driven demand forecasting, inventory optimisation, and automated replenishment systems. The logic of the research involved a step-by-step transition from the analysis of the transformation of the product policy paradigm under conditions of digitalisation to the development of a comprehensive AI-driven management model.

Results and Discussion

Analysis of the application of artificial intelligence in product policy optimisation and inventory management

The management of product policy in modern enterprises increasingly depends on the volume and quality of data that form the foundation for managerial decision-making in retail. Within the traditional paradigm, product management relied on statistical estimations, market intuition, and the professional experience of specialists. However, the increasing speed of market changes, the growing number of SKUs, and the rising instability of demand have created a critical need to transition toward algorithm-based decision-making systems. In this context, data become a strategic asset that enables the generation of accurate demand forecasts, optimisation of assortment structures, and the continuity of product flows within retail networks. The study of O. Amosu *et al*. (2024) confirmed that the use of AI-driven forecasting systems significantly enhances predictive accuracy, reduces the risk of stock-outs and excess inventory, and improves inventory turnover in retail environments. For instance, the recommendation system of Amazon, which relies on large-scale predictive analytics and machine learning models that analyse browsing behaviour, purchase history, and customer preferences, generates approximately 35% of the company's total sales, illustrating the substantial commercial impact of algorithm-based product management decisions (Kuprenko, 2024). At the same time, the broader adoption of predictive analytics technologies across the retail sector enables firms to achieve 15-30% growth in sales through personalised recommendations, 20-50% reductions in inventory costs, and 30-60% improvements in demand forecasting accuracy, thereby significantly enhancing the efficiency of assortment management and supply chain coordination (Kinha, 2025).

An important aspect is the diversity of data sources that form the informational basis of product policy. Transactional data reflect real consumer behavioural patterns, logistics data make it possible to evaluate supply cycles, while competitive data obtained through monitoring systems ensure the adaptability of pricing and assortment strategies. The concept of a "single source of truth", widely adopted in contemporary retail systems, implies the integration of all data into a unified system while minimising duplication and distortion. This creates the necessary conditions for the effective use of machine learning algorithms, which require large volumes of structured data (Lytiuha & Kotyk, 2024). Artificial intelligence plays a crucial role in demand forecasting, as it is capable of modelling complex nonlinear relationships that remain inaccessible to traditional statistical methods. The most commonly used models in retail include Random Forest, Gradient Boosting, XGBoost, and recurrent neural networks such as LSTM or Hybrid (XGBoost + LSTM), which enable the consideration of seasonality, promotional activities, behavioral anomalies, and external factors. In contrast, traditional statistical approaches such as ARIMA and exponential smoothing are generally more effective in relatively stable forecasting environments but have limited capacity to capture nonlinear relationships and rapidly changing demand patterns. The comparison of these approaches was conducted based on forecasting accuracy, the ability to capture nonlinear dependencies, and adaptability to volatile market conditions (Table 1).

Table 1. Comparison of traditional statistical and machine learning models in retail demand forecasting

Model	Type	RMSE*	MAE*	MAPE*, %	Forecasting accuracy	Nonlinearity	Volatility adaptation	Seasonality handling	Scalability for large retail datasets	Capacity for real-time model updating	Key empirical evidence
ARIMA	Statistical	High	Medium	15-25	Medium	Low	Low	Good	Low-Medium	Low	Limited performance with nonlinear demand; outperformed by ML models
Exponential smoothing (ETS)	Statistical	Medium-High	Medium	12-20	Medium	Low	Low-Medium	Good	Medium	Low	Effective in stable time series but limited in complex patterns
Random Forest	Machine learning	Medium	Medium-Low	10-15	High	Medium-High	Medium	Limited	High	Medium	Improves accuracy through ensemble learning approaches
Gradient boosting	Machine learning	Medium-Low	Low	8-12	High	High	High	Limited	High	Medium	High predictive accuracy due to iterative error minimisation
XGBoost	Machine learning	Low	Low	5-10	Very High	Very High	High	Limited	Very high	High	Achieves superior performance ($R^2 \approx 0.95$) in retail forecasting
LSTM	Deep learning	Very Low	Low	3-8	Very High	Very High	Very High	Excellent	Medium	High	Captures complex temporal dependencies and nonlinear patterns
Hybrid (XGBoost + LSTM)	Hybrid AI	Lowest	Lowest	2-5	Highest	Very High	Very High	Excellent	High	Very high	Reduces forecasting error by 15-20% vs single models; improves RMSE up to 45%

Note: *the values of RMSE, MAE, and MAPE are generalised ranges derived from empirical studies in retail demand forecasting and may vary depending on dataset characteristics, time horizon, and feature engineering approaches

Source: completed by the authors based on I. Tarallo *et al.* (2019), M. Nasseri *et al.* (2023), K. Douaioui *et al.* (2024), S. Ankam (2025), A. Balusani *et al.* (2025), D. Suganthi *et al.* (2025), B. Wang & A. Zain (2025)

The studies I. Tarallo *et al.* (2019) and S. Ankam (2025) confirmed that such models provide significantly higher forecasting accuracy compared with traditional approaches such as ARIMA or exponential smoothing, particularly under conditions of volatile market environments, emphasising the role of predictive analytics in improving demand forecasting and supply chain responsiveness in enterprise retail systems. I. Tarallo *et al.* (2019) demonstrated that machine learning models provide more accurate forecasts in retail environments compared to traditional statistical models, particularly when demand is influenced by multiple external and behavioural factors. Similarly, K. Douaioui *et al.* (2024) showed that machine learning and deep learning approaches outperform classical methods in dynamic supply chain conditions due to their ability to process large datasets and adapt to changing demand patterns. An additional advantage of AI is the ability to adapt models in real time, which is particularly important in FMCG sectors where demand frequently changes under the influence of macro- and micro-level trends.

Automated forecasting systems are actively applied by leading retail chains such as Walmart, Tesco, and RELEX Solutions, where machine learning algorithms are used not only to predict sales volumes but also to optimise ordering frequency, product distribution, and inventory levels across stores of different formats (Kaleva & Småros, n.d.). Compared to traditional forecasting approaches, which typically rely on historical sales data and assume relatively stable demand patterns, machine learning-based systems are capable of incorporating a wider range of variables, including promotional activities, external factors, and consumer behaviour dynamics. This enables higher forecasting accuracy and more flexible inventory management, particularly in environments characterised by demand volatility and frequent assortment changes. In contrast, traditional statistical models are less effective in capturing such complexity, which limits their applicability in modern retail systems. Practical evidence and prior studies indicate that the implementation of AI-driven forecasting and inventory optimisation systems contributes to improved inventory management performance, including lower stock-out risks, reduced excess inventory, and enhanced inventory turnover in retail environments (Tarallo *et al.*, 2019; Kaleva & Småros, n.d.).

Assortment optimisation represents the second key direction of AI application in product policy. Clustering algorithms make it possible to identify the core assortment, meaning those items that generate the largest share of turnover and ensure stable demand. Another important task is the identification of low-profit or redundant SKUs that overload shelves and complicate logistics processes. AI models can analyse product profitability, purchase frequency, cross-demand relationships between products, and consumer responses to promotional campaigns, thereby generating recommendations regarding the reduction or expansion of the assortment. For example, Y. Yu *et al.* (2024) demonstrated that data-driven assortment optimisation supports the identification of product combinations associated with stronger consumer demand and higher market value. In this way, AI-based models help retailers distinguish high-performing items from low-profit or redundant SKUs and adjust assortment structures accordingly. Particular attention should be paid to the omnichannel logic of assortment formation, since online and offline channels demonstrate different demand patterns. In such cases, artificial intelligence enables the coordination of SKUs across channels, the formation of optimal product sets, and the prevention of product cannibalisation.

Inventory management represents another essential component of product policy. AI technologies enable the automated generation of replenishment orders (auto-replenishment) based on demand forecasts, replenishment cycles, and service level indicators. For example, Increff's inventory optimisation platform utilises predictive analytics to dynamically adjust reorder quantities and timings based on realtime demand patterns, service level targets, and SKUlevel forecasts, reducing overstock and stockouts without manual intervention (Smart merchandising…, n.d.). Similarly, AI-powered software such as Leafio automatically calculates optimal reorder points and quantities by integrating forecasted demand, inventory buffers, and supplier constraints, resulting in significant reductions in excess inventory and improved product availability (AI-powered automated inventory…, n.d.). FieldAssist's autoreplenishment system, implemented at scale in FMCG retail chains, has demonstrated tangible improvements in service levels and shelf availability by automatically generating replenishment orders from demand forecasts and actual sales data (End stock guesswork…, n.d.). Platforms like Optiply further extend this capability by generating fully automated purchase orders to suppliers via EDI and other channels, contributing to measurable increases in service levels and reductions in lost sales due to stock shortages (From manual work…, n.d.). Such systems allow for more accurate determination of reorder points, prevention of stock shortages, and avoidance of excessive procurement, which is particularly important in highly competitive sectors. The integration of demand forecasting with logistics algorithms makes it possible to synchronise warehouse inventories with actual sales and supplier capabilities, thereby minimising fluctuations and operational costs.

AI-driven product policy model in retail: Analysis and integration

Based on the conducted analysis, it is appropriate to develop a comprehensive AI-driven product policy model that generalises the identified patterns, systematises the interaction of key elements of product management, and functions as a cyclical self-regulating system (Fig. 1), integrating forecasting, optimisation, and automation into a unified decision-making framework.

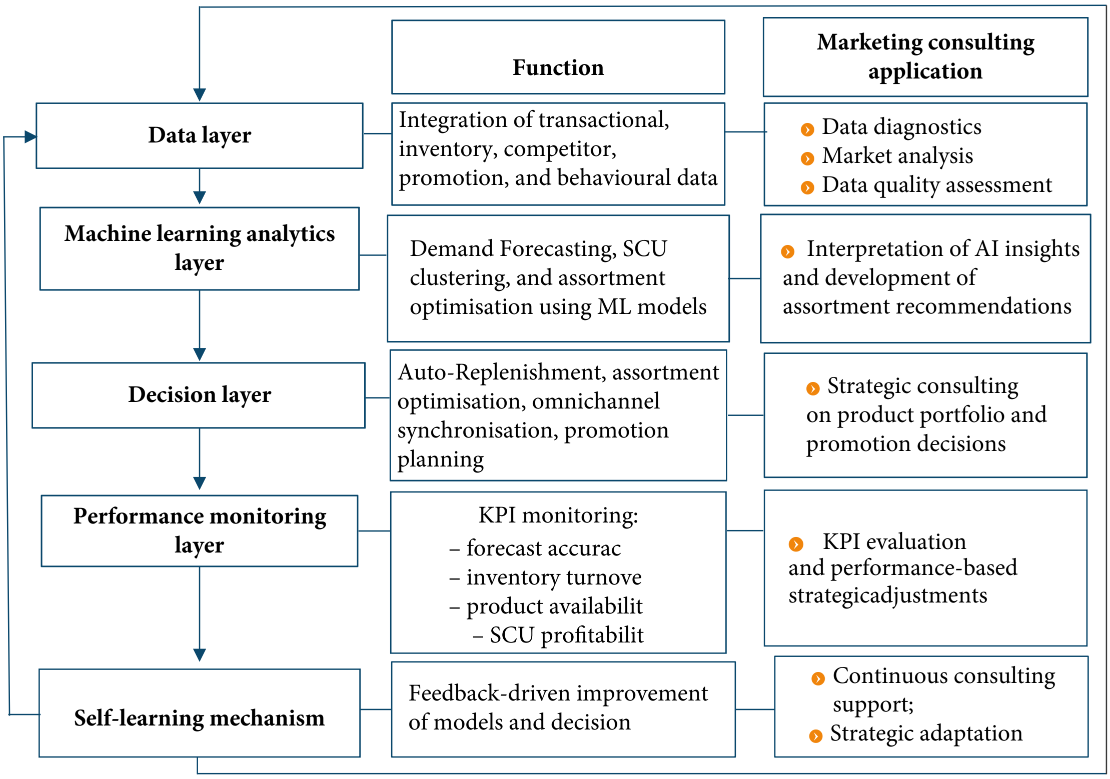

Figure 1. Conceptual multi-level model of AI-driven product policy and marketing consulting integration
Source: developed by the authors

As illustrated, the proposed AI-driven product policy model represents a multi-level integrated system in which all stages of assortment management are combined into a single adaptive decision-making cycle. The model is based on the synergistic interaction of three key components: data, artificial intelligence algorithms, and managerial decision-making, which together form a closed loop of continuous optimisation of the enterprise's product policy. The key advantage of the model lies in its ability to ensure the dynamic adaptation of product policy in real time, improving forecasting accuracy, enhancing the validity of managerial decisions, and increasing the flexibility of responses to changes in demand, the competitive environment, and consumer behaviour under conditions of high market turbulence.

At the first level of the model, data are collected, aggregated, and cleaned. These data include transactional information, inventory data, competitor pricing, promotional activities, logistical parameters, and consumer behavioural characteristics. This stage ensures the formation of a unified information dataset suitable for further analytics and modelling, while also providing the analytical foundation for marketing consulting support. The second level involves analytical data processing using machine learning algorithms. Within this stage, demand forecasts are generated (using models such as Gradient Boosting, Random Forest, and LSTM), product clustering is performed, profitability is evaluated, and the optimal assortment structure is determined. The results obtained provide the analytical basis for interpretation within marketing consulting and for the development of managerial recommendations. AI enables the model to adapt to demand instability, seasonal fluctuations, and changes in consumer behaviour.

The third level of the model encompasses operational decision-making processes, including automated order generation (auto-replenishment), inventory optimisation, identification of priority SKUs for promotional activities, and synchronisation of assortments across online and offline channels. At this stage, the results of AI analytics are transformed into specific managerial actions, while marketing consulting performs a methodological support function for implementing and adapting decisions to the specific characteristics of the enterprise. The fourth level focuses on performance control and evaluation based on a system of key performance indicators (KPIs), including forecasting accuracy, inventory turnover, product availability levels, SKU profitability, and the speed of response to changes in demand. These indicators are fed back into the system as a feedback mechanism, ensuring its self-learning and evolutionary development, while also forming an analytical platform for further consultative decisions. Thus, AI technologies enable the formation of a holistic model of product policy, which creates an analytical foundation for marketing consulting aimed at optimising product policy, improving operational efficiency, and increasing enterprise profitability. Within such a model, decisions are made on the basis of data, and all stages – from data collection to automated replenishment – are integrated into a unified management system. In this context, KPI indicators become more precise and accurately reflect the real state of operational processes, including inventory turnover, product availability, profitability, and forecasting accuracy.

The application of AI in assortment formation makes it possible to reduce the number of unprofitable SKUs and increase overall enterprise profitability. The integration of AI with logistics and managerial systems also improves service levels, reduces the likelihood of shortages and excess inventory, and ensures more accurate replenishment processes. As a result, companies can adapt more rapidly to market changes, reduce operational costs, and increase profitability. At the same time, despite the significant potential of artificial intelligence technologies, their practical implementation in product policy management is accompanied by several systemic barriers. One of the main challenges is the lack of high-quality data, which often contain missing values, duplicates, or errors, thereby reducing the effectiveness of predictive models. Furthermore, integrating AI into existing ERP, CRM, and Warehouse Management Systems is technologically complex and requires a high level of digital maturity within the organisation. Another important issue is the shortage of qualified personnel, since the functioning of AI models requires the involvement of data analysts, data engineers, and machine learning specialists, who represent scarce professional profiles in the modern labour market. Ethical risks should also be noted, particularly those related to algorithmic transparency and potential biases in analytical outcomes, which create an additional set of challenges requiring regulatory oversight and responsible implementation of technological solutions.

Therefore, the results obtained indicate that the implementation of an AI-driven product policy model in the Ukrainian retail sector faces specific limitations that are not fully reflected in international studies. Unlike approaches presented in the work of R. Hyndman & G. Athanasopoulos (2021), which focused primarily on improving forecasting accuracy through algorithmic refinement, the findings of this study demonstrate that for Ukrainian retail networks the critical factor is not the complexity of the algorithm itself but rather the quality and standardisation of data. Data inconsistency, fragmentation, and the absence of unified reference directories significantly reduce the stability of predictive models, which highlights the need for methodological approaches to data cleaning, standardisation, and validation, particularly through the implementation of Master Data Management systems.

The results of the study also confirm that the effectiveness of AI-driven product policy depends not only on the choice of forecasting algorithm but also integration of data, analytical models, and managerial procedures. K. Douaioui *et al.* (2024) and R. Ahmed *et al.* (2024) demonstrated that machine learning (ML) and deep learning (DL) models significantly outperform traditional statistical methods, particularly in retail environments characterised by high variability and complex, multifactorial dynamics. Hybrid architectures such as LSTM, Convolutional Neural Network-LSTM, and ensemble algorithms provide higher forecasting accuracy in time-series sales data and allow the incorporation of seasonality, promotional activity, and behavioural factors. At the same time, the findings of this research are consistent with systematic reviews on the comprehensive highlighting the role of AI in transforming supply chains. A. Teixeira *et al.* (2025) emphasised that the key determinant of model success is the quality of data and their integration into a unified enterprise information architecture. For Ukrainian retail networks, this issue is particularly relevant due to fragmented reference systems and heterogeneous accounting infrastructures, which confirms the importance of implementing Master Data Management approaches as a basis for the stable functioning of AI algorithms.

Further development of AI applications concerns not only demand forecasting but also the formation of strategic decisions in product policy, including the optimisation of assortment structures and inventory management. M. Karim (2025) demonstrated that AI-enhanced predictive analytics enables the integration of spatial and temporal demand patterns, thereby increasing inventory adaptability to local market conditions. Similar findings were obtained by A. Chowdhury *et al.* (2025), who showed that the implementation of machine learning algorithms reduces both stock shortages and excess inventory in multi-channel retail environments. At the same time, the results of this study highlight the importance of implementing Explainable AI in the field of product policy management. While highly accurate models demonstrate strong predictive potential, their lack of transparency may create barriers for strategic management. K. Douaioui *et al.* (2024) highlighted that combining forecasting accuracy with model interpretability is essential for effective managerial decision-making in inventory and pricing management. Moreover, A. Fatima & M. Salam (2026) indicated the promising potential context-aware predictive models, which incorporate external factors such as weather conditions, calendar events, and socio-economic changes in order to improve forecasting accuracy. This confirms the necessity of transitioning from isolated predictive models to comprehensive multi-level systems that integrate data from various sources within a unified adaptive product policy management cycle.

The findings of the present study further highlight the "black box" problem of machine learning algorithms, as identified by C. Rudin (2019) and V. Hassija *et al.* (2023). In the context of product policy management, strategic interpretability of analytical results becomes particularly important, going beyond mere technical transparency to enable verification of algorithmic recommendations against the long-term objectives of assortment and pricing strategies. Another direction of discussion concerns the growing role of generative artificial intelligence in driving innovation and strategic decision-making in product policy. P. Cillo & G. Rubera (2025) argued that generative AI technologies, beyond their common application in content creation, have considerable potential to support innovation processes by enabling firms to generate novel product concepts, simulate virtual SKUs, test potential market niches, and explore consumer trends before actual product launches, thus enhancing the agility and creativity of marketing and product management strategies.

Building on this perspective, multi-agent approaches have emerged as a complementary mechanism for coordinating complex operations and decision-making in supply chains, integrating forecasting, logistics, inventory, and pricing functions into adaptive product management systems. L. Xu *et al.* (2023) demonstrated that multi-agent approaches play a crucial role in supply chain and product management by enabling the integration of demand forecasting, logistics, inventory management, and pricing within adaptive supply chain networks. Empirical studies of A. Zulfia *et al.* (2025) also demonstrated the practical effectiveness of AI solutions in real retail environments. The authors developed a decision support system based on Random Forest, which proved to be an effective tool for demand forecasting and inventory management in dynamic urban markets. One of the trends is the integration of association rules with machine learning, which provides more flexible forecasting mechanisms under conditions of unpredictable consumer behaviour. For example, M. An *et al.* (2025) demonstrated how Association Rule-based Machine Learning can improve forecasting quality in micro-fulfilment centres, where traditional ML methods may be less accurate due to high variability in data. Thus, AI in product policy is evolving from a forecasting tool to a system-forming element of assortment, inventory, and pricing management, while the explainability of algorithms becomes not merely a technical issue but a strategic factor in product management. At the same time, the practical effectiveness of such models in retail networks ultimately depends on the combination of high-quality data infrastructure, interpretable algorithms, and an integrated management architecture.

Conclusions

The study substantiated and developed a comprehensive model of AI-driven product policy that conceptualises the interaction between data, algorithms, and managerial decision-making in retail and serves as a methodological platform for marketing consulting aimed at implementing intelligence-supported managerial decisions. The model interpreted product policy as a multi-level system in which machine learning enables demand forecasting, assortment structuring, and inventory optimisation, while data provide the informational foundation for its adaptability and dynamic development. The significance of the proposed model lies in the transformation of the logic of product policy management from a static set of managerial tools to an evolutionary cycle incorporating elements of self-learning. Such an approach creates new opportunities for the consultative support of retail enterprises and forms the prerequisites for using marketing consulting as a mechanism for integrating AI solutions into managerial practice, substantiating strategic transformations, and evaluating their effectiveness. The developed model also made it possible to identify the potential for reducing operational costs, improving the accuracy of strategic planning, and strengthening the resilience of business processes. At the same time, it serves as an instrumental framework for developing recommendations within the context of marketing consulting. Promising directions for the further development of the model include the implementation of multi-agent AI systems, increasing the transparency of forecasting algorithms, and integrating real-time data processing into product flow management systems.

Thus, the implementation of artificial intelligence in product policy becomes not only a tool for responding to market changes but also a foundation for building sustainable competitive advantages. It ensures the substantiation of assortment and market-product strategies on the basis of analytical patterns rather than intuitive assumptions, thereby creating conditions for the effective use of marketing consulting in the development of strategically grounded managerial decisions. Prospects for further research in the field of AI applications in product policy are extensive and include both theoretical and practical aspects of improving demand and assortment management models. One of the key issues requiring further investigation is the integration of hybrid demand forecasting models combining machine learning algorithms with traditional econometric approaches. Such integration may contribute to the development of more flexible and resilient predictive systems capable of operating effectively under conditions of market instability, increased volatility, and frequent structural changes in consumer behaviour.

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Conflict of Interest

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Модель AI-керованої товарної політики роздрібних мереж як концептуальна основа маркетингового консультування

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Анотація. Активний розвиток омніканальних систем збуту, а також необхідність підвищення швидкості й точності маркетингових рішень у товарній політиці зумовлюють потребу впровадження алгоритмічних методів аналізу даних і технологій штучного інтелекту, що особливо важливо для підприємств ритейлу в умовах високої ринкової конкуренції, динамічних змін споживчого попиту та необхідності ухвалення гнучких екстрених рішень. Мета дослідження полягала в розробленні теоретико-методологічних засад управління товарною політикою підприємств роздрібної торгівлі шляхом проєктування концептуальної багаторівневої моделі товарної політики на основі штучного інтелекту. Дослідження ґрунтувалося на поєднанні загальнонаукових і спеціальних методів, зокрема, аналізу та синтезу, порівняльного аналізу, системного аналізу, структурно-логічного моделювання, абстрагування та узагальнення. Здійснено теоретичне обґрунтування переходу до AI-керованої товарної політики через визначення системоутворювальної ролі даних у процесі ухвалення маркетингових рішень аналіз можливостей алгоритмів машинного навчання та конкретизацію напрямів їх застосування у прогнозуванні попиту, оптимізації асортименту й автоматизованого управління запасами. Розроблено, структуровано та обґрунтовано багаторівневу модель AI-керованої товарної політики, що функціонує як цілісна замкнена система із механізмом зворотного зв’язку і поєднує етапи збору та інтеграції даних, алгоритмічне прогнозування та AI-аналітику, управлінські рішення з оптимізації асортименту, автоматизованого управління запасами, KPI-моніторинг результативності. Визначено переваги запропонованої моделі, практичні результати від її впровадження та системні бар’єри реалізації AI-рішень. Практична цінність дослідження полягає у можливості використання розробленого підходу як методичного інструментарію маркетингового консультування для підвищення адаптивності суб’єктів ритейлу, зниження операційних витрат, прискорення товарообороту та формування стійких конкурентних позицій на основі data-driven управління

Ключові слова: маркетингові рішення; маркетингове планування; data-driven управлінське консультування; цифрова аналітика; товарний портфель; ринково-продуктова стратегія; омніканальна роздрібна торгівля