Mechanism for developing the assortment policy of e-commerce enterprises based on generative artificial intelligence

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Abstract. The study is aimed at developing a mechanism for forming the assortment policy of e-commerce enterprises based on generative artificial intelligence. The research examines how Generative AI can be integrated with demand forecasting, customer analytics, inventory information, product data, and managerial control to support economically justified decisions on the composition and adjustment of an online assortment.

The methodological basis combined the analysis and synthesis of research on assortment optimisation, retail forecasting, machine learning, recommender systems, generative artificial intelligence, and human-AI decision-making. On this basis, the information architecture of assortment management was structured, and a seven-stage mechanism was developed. It includes data acquisition, analytical processing, generative interpretation, generation of assortment alternatives, economic evaluation, managerial validation, and feedback. The mechanism integrates transaction data, customer behaviour, reviews and search queries, product and category characteristics, inventory indicators, competitor information, and market signals.

The results showed that Generative AI should not substitute conventional forecasting, optimisation, or recommendation models. Its appropriate function is that of an interpretive and decision-support layer that combines heterogeneous information and converts it into five types of assortment alternatives: add, retain, expand, reduce, and remove. Each alternative should subsequently be evaluated according to expected demand, profitability, inventory turnover, conversion potential, operational feasibility, competitive position, and strategic fit. Managerial validation remains mandatory because generative models may produce unreliable interpretations and cannot independently account for all operational and strategic constraints.

The scientific novelty lies in the development of an integrated mechanism in which Generative AI connects specialised analytical tools with economic evaluation and human managerial control within a single assortment decision cycle. The practical value of the results consists in the possibility of applying the proposed mechanism for continuous adjustment of e-commerce product portfolios, identification of unmet demand, reduction of redundant assortment positions, and improvement of the economic justification of SKU and category decisions.

Keywords: e-commerce, assortment policy, generative artificial intelligence, assortment optimisation, demand forecasting, customer behaviour, recommender systems, inventory management, managerial decision-making, human-in-the-loop.

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Механізм формування асортиментної політики підприємств електронної комерції на основі генеративного штучного інтелекту

Анотація. Метою дослідження є розроблення механізму формування асортиментної політики підприємств електронної комерції на основі генеративного штучного інтелекту. У роботі визначено, яким чином Generative AI може бути інтегрований із прогнозуванням попиту, аналітикою поведінки споживачів, інформацією про запаси, характеристиками товарів і управлінським контролем для підтримки економічно обґрунтованих рішень щодо складу та коригування онлайн-асортименту.

Методологічну основу становили аналіз і синтез досліджень з оптимізації асортименту, прогнозування роздрібного попиту, машинного навчання, рекомендаційних систем, генеративного штучного інтелекту та взаємодії людини і ШІ у процесі прийняття управлінських рішень. На цій основі структуровано інформаційну архітектуру асортиментного управління та розроблено семиетапний механізм, який охоплює збір даних, аналітичну обробку, генеративну інтерпретацію, формування асортиментних альтернатив, економічне оцінювання, управлінську валідацію та зворотний зв'язок. Механізм об'єднує транзакційні дані, поведінкову інформацію, відгуки й пошукові запити, характеристики товарів і категорій, показники запасів, дані про конкурентів та ринкові сигнали.

Встановлено, що Generative AI не повинен замінювати традиційні моделі прогнозування, оптимізації чи рекомендаційні системи. Його доцільно використовувати як інтерпретаційний і підтримувальний рівень, який поєднує різнорідні інформаційні сигнали та трансформує їх у п'ять типів асортиментних альтернатив: додати, зберегти, розширити, скоротити або вилучити товарну позицію. Кожна альтернатива має надалі оцінюватися за очікуваним попитом, прибутковістю, оборотністю запасів, потенціалом конверсії, операційною здійсненністю, конкурентною позицією та стратегічною відповідністю. Управлінська валідація залишається обов'язковою, оскільки генеративні моделі можуть створювати ненадійні інтерпретації та не здатні автономно врахувати всі операційні й стратегічні обмеження підприємства.

Наукова новизна полягає у розробленні інтегрованого механізму, в якому Generative AI поєднує спеціалізовані аналітичні інструменти з економічним оцінюванням і управлінським контролем у межах єдиного циклу формування асортиментних рішень. Практична цінність результатів полягає у можливості застосування запропонованого механізму для безперервного коригування товарного портфеля підприємств електронної комерції, виявлення незадоволеного попиту, скорочення надлишкових асортиментних позицій та підвищення економічної обґрунтованості рішень на рівні SKU і товарних категорій.

Ключові слова: електронна комерція, асортиментна політика, генеративний штучний інтелект, оптимізація асортименту, прогнозування попиту, поведінка споживачів, рекомендаційні системи, управління запасами, управлінські рішення, human-in-the-loop.

Introduction

Relevance of the problem. Assortment policy in e-commerce is no longer limited to determining the breadth and depth of a product portfolio or periodically revising the number of stock-keeping units. An online enterprise operates with large and continuously changing product catalogues, heterogeneous demand patterns, customer search histories, transaction data, reviews, competitive offers, inventory constraints, and rapidly changing preferences. Under these conditions, an assortment decision involves several interconnected choices: which products should be introduced, retained, expanded, reduced, repositioned, or removed from the catalogue. Classical assortment planning models provide a rigorous basis for such decisions, particularly when consumer search, basket composition, demand substitution, and category interactions are taken into account [1; 2]. However, their practical implementation becomes more complicated when the number of available products and information signals grows and when customer behaviour changes faster than manually designed assortment rules can be revised.

The development of data-driven retailing has partially addressed this problem. Demand forecasting, machine learning, customer choice modelling, and marketing analytics make it possible to identify regularities in sales and consumer behaviour that would be difficult to detect through conventional managerial analysis. In particular, machine-learning models can support product display decisions in large online marketplaces [10], while high-dimensional choice models allow online retailers to process extensive behavioural information when estimating consumer demand [19]. Retail forecasting techniques have also progressed from conventional statistical approaches towards models capable of dealing with large numbers of SKUs, promotional variables, and heterogeneous explanatory factors [11; 24; 25; 34]. Yet these approaches predominantly predict, classify, rank, or optimise within a predefined analytical structure. They do not by themselves provide a unified mechanism for interpreting heterogeneous textual and quantitative signals and translating them into economically justified alternatives for assortment policy.

Generative artificial intelligence changes this configuration. Unlike traditional predictive models, generative AI and large language models can process unstructured information, interpret textual context, summarise dispersed signals, formulate alternative scenarios, and support interaction between analytical systems and decision-makers [9; 21; 22]. For an e-commerce enterprise, this creates the possibility of combining transaction histories, customer reviews, search queries, product descriptions, competitor information, demand forecasts, and inventory indicators within a single decision-support environment. Accordingly, generative AI can potentially become not merely an additional recommendation technology but a semantic and analytical layer connecting market information with assortment decisions. The relevance of the problem therefore lies in the need to determine how this technological capability can be embedded in an economically controlled mechanism of assortment policy formation rather than implemented as an isolated content-generation or recommendation tool.

Analysis of recent research and publications. Research on assortment management has developed several complementary directions. The first is represented by classical assortment planning and optimisation. G. P. Cachon and A. G. Kök examined coordination problems in retail assortment planning under basket-shopping behaviour [1], while G. P. Cachon et al. considered assortment decisions in the presence of consumer search [2]. M. K. Mantrala et al. demonstrated that assortment planning remains difficult because retailers must simultaneously account for consumer preferences, category structure, operational constraints, and economic performance [26]. Dynamic assortment planning was further developed by D. Sauré and A. Zeevi, who incorporated demand learning into assortment decisions [28]. More recent studies extend this logic to omnichannel retailing and interactions between assortment and inventory. J. Hense and A. H. Hübner analyse assortment optimisation across retail channels [14], S. Transchel et al. integrate assortment and inventory decisions under consumer substitution [30], while A. Vasilyev et al. examine assortment optimisation in an omnichannel environment [32]. The systematic review by J. Heger and R. Klein confirms that assortment optimisation has developed into a broad research field with diverse demand models, constraints, and solution approaches [13]. Evidence from digital retail settings further demonstrates that assortment decisions cannot be separated from the specific characteristics of online sales channels. S. Fedoseeva and R. Herrmann show that assortment composition and pricing are closely interconnected in online grocery retailing [8], while X. Tian et al. provide evidence that product assortment is directly associated with online sales performance in community group-buying channels [29].

These findings reinforce the need to consider assortment policy not only as an optimisation problem but also as an economically consequential element of digital commerce. Nevertheless, much of this literature remains centred on mathematically specified choice structures and optimisation procedures rather than on generative interpretation of heterogeneous commercial data.

The second direction concerns data-driven forecasting, customer analytics, and machine learning. R. Fildes et al. demonstrate the growing methodological diversity of retail forecasting and emphasise the operational importance of accurate demand estimates [11]. S. Ma and R. Fildes apply meta-learning to retail sales forecasting [24], whereas S. Ma et al. address SKU-level forecasting with high-dimensional promotional information [25]. A. P. Wellens et al. show how tree-based methods can incorporate explanatory variables into retail sales forecasts [34]. At the level of consumer choice and online product presentation, J. Feldman et al. compare choice models with machine-learning approaches using the context of Alibaba product displays [10]. Z. Jiang et al., meanwhile, develop a high-dimensional choice model for online retailing [19]. A related direction is the use of statistical learning for personalised economic decisions. X. Chen et al. demonstrate that customer-level information can be incorporated into revenue-management models to support differentiated decisions under heterogeneous consumer behaviour [4]. This approach is relevant to assortment formation because the economic value of a product cannot always be inferred from aggregate demand alone; customer heterogeneity may alter the expected contribution of individual assortment positions. These studies are particularly relevant for assortment policy because they demonstrate that product decisions can be based on increasingly granular behavioural data. Their analytical logic, however, is predominantly predictive: the model estimates expected demand, choice, or sales response, while the subsequent transformation of these estimates into a broader assortment policy remains a managerial task.

The third research direction concerns the application of artificial intelligence and generative models in marketing and electronic commerce. T. H. Davenport et al. conceptualise artificial intelligence as a technology capable of changing marketing processes and managerial functions [6], while M.-H. Huang and R. T. Rust propose a strategic framework for integrating AI into marketing activities [16]. The emergence of generative AI has widened this discussion considerably. S. Feuerriegel et al. distinguish generative AI from earlier analytical approaches by its ability to generate new content and interact with complex contextual inputs [9]. N. Kshetri examines generative AI specifically in the context of e-commerce [21], and N. Kshetri et al. identify its applications, opportunities, and managerial challenges in marketing [22]. The transition from predictive to generative AI also changes the way consumer information can be interpreted. E. Hermann and S. Puntoni distinguish the implications of predictive and generative AI for consumer behaviour, showing that generative systems extend the analytical setting beyond prediction towards interaction and contextualised response generation [15]. At the application level, D. Chakraborty et al. demonstrate the relevance of generative AI chatbots for trust formation in online grocery shopping [3]. Although these studies do not directly address assortment optimisation, they indicate that generative systems can process and mediate customer-facing information that is potentially valuable for identifying preferences, concerns, and unmet demand. P. Cillo and G. Rubera further associate generative AI with transformations in innovation and marketing processes [5], whereas D. Grewal et al. consider its implications for the future configuration of marketing activities [12]. Collectively, these works show a transition from AI used primarily for prediction and automation towards AI capable of interpretation, generation, and interactive decision support.

A closely related stream focuses on recommender systems and large language models. L. Li et al. examine the development of generative recommendation based on large language models [23], while L. Wu et al. systematise the emerging literature on LLMs for recommendation [35]. Z. Zhao et al. similarly demonstrate how recommender-system architectures are being reconsidered in the era of large language models [36]. These developments are highly relevant to e-commerce, but recommendation and assortment policy should not be treated as synonymous. A recommender system primarily addresses the problem of which available product should be presented to a particular customer. Assortment policy addresses a broader economic question: which products should be present in the enterprise's portfolio at all, in what proportions, and under what conditions they should be introduced, retained, expanded, reduced, or removed. Consequently, LLM-based recommendation provides an important technological component, but it does not constitute a complete mechanism of assortment policy formation.

The fourth direction concerns the organisational limits of AI-supported decisions. M. H. Jarrahi interprets human-AI interaction as a form of symbiosis in organisational decision-making [17], while S. Raisch and S. Krakowski distinguish between automation and augmentation as alternative but interconnected roles of artificial intelligence in management [27]. This distinction is especially important for assortment decisions, where a technically generated recommendation must still be evaluated against profitability, inventory capacity, strategic positioning, and managerial constraints. In addition, generative systems introduce risks associated with unreliable or fabricated outputs. Z. Ji et al. systematise the hallucination problem in natural language generation [18]. For this reason, generative AI cannot reasonably be treated as an autonomous decision-maker in assortment management. Its role is more appropriately understood as a controlled analytical layer whose outputs are subjected to economic filters and managerial validation.

Unresolved issues of the problem. Despite substantial progress in assortment optimisation, retail forecasting, machine learning, recommender systems, and generative AI, these research streams remain insufficiently integrated. Existing assortment models predominantly optimise product portfolios using predefined demand and choice structures [13; 14; 28; 30], whereas studies of generative AI focus mainly on marketing communication, recommendation, content generation, or broader transformations of e-commerce [5; 9; 21; 22; 35; 36]. As a result, the literature does not yet provide a sufficiently developed economic mechanism in which generative AI systematically transforms heterogeneous e-commerce data into assortment-policy alternatives and then subjects those alternatives to profitability, demand, inventory, risk, and strategic constraints.

The unresolved issue is therefore not whether generative AI can process commercial information, but how its capabilities should be incorporated into a controlled sequence of assortment decisions. Such a mechanism should connect sales and behavioural data, customer reviews and search queries, competitive and market signals, demand forecasts, inventory indicators, semantic interpretation, generation of assortment alternatives, economic assessment, managerial validation, and subsequent feedback from actual sales performance. In this configuration, generative AI should not replace forecasting models, recommendation systems, inventory management tools, or human decision-makers. Rather, it should coordinate and interpret their outputs within a common decision-support architecture.

Aim of the article is to develop a mechanism for forming the assortment policy of e-commerce enterprises based on generative artificial intelligence, which integrates heterogeneous market and enterprise data, demand forecasting, semantic interpretation of unstructured information, generation of alternative assortment decisions, economic evaluation, managerial validation, and feedback from actual commercial results. The proposed mechanism is intended to support decisions on the introduction, retention, expansion, reduction, and removal of products and product categories while preserving managerial control over the final assortment configuration.

Results

Analytical basis for GenAI-supported assortment policy. The analysis indicates that assortment policy in e-commerce should be considered as a continuous decision process rather than a periodic revision of the product catalogue. Traditional assortment models primarily address the selection of products under consumer choice, search, demand, and resource constraints [1; 2; 28]. More recent approaches integrate assortment decisions with omnichannel operations and inventory management [14; 30; 32]. The systematic review by Heger and Klein [13] confirms that assortment optimisation has developed into a broad field combining consumer choice, demand estimation, operational constraints, and mathematical optimisation.

However, the e-commerce environment introduces substantially more heterogeneous information. Enterprises simultaneously receive signals from sales, searches, clicks, product views, reviews, inventory levels, competitor activity, and marketplace dynamics. Machine-learning models improve the processing of such information through forecasting, classification, ranking, and consumer-choice estimation [10; 11; 19; 24; 25]. Nevertheless, these outputs remain predominantly task-specific. Multi-channel operations further complicate assortment decisions – the same product may perform differently on Amazon, Walmart, Home Depot, and a proprietary D2C storefront, requiring channel-specific assortment considerations.

Generative AI provides an additional decision-support capability. It can interpret structured analytical outputs together with textual and contextual information, identify relationships between signals, explain deviations, and generate alternative assortment scenarios [9; 21; 22]. Thus, its main role in assortment policy is not to replace forecasting or optimisation but to connect heterogeneous information with economically interpretable managerial alternatives. The mechanism proposed below draws on observations from production e-commerce operations at a mid-sized North American multi-channel retailer serving eight major marketplace channels.

Table 1

Transformation of analytical support for assortment policy

Approach	Main data	Primary function	Output for assortment management
Traditional assortment planning	Sales, categories, prices	Selection of products	Defined SKU/category set
Predictive analytics	Historical demand, promotions, seasonality	Demand forecasting	Expected sales and demand
Machine learning	Behavioural and transactional data	Prediction, ranking, choice modelling	Product scores and behavioural patterns
Recommender systems	Customer-product interactions	Personalisation	Ranked products for individual customers
Generative AI	Structured and unstructured data	Interpretation and scenario generation	Contextualised assortment alternatives

Source: developed by the author based on [1; 2; 9; 10; 13; 21; 22; 28].

An important distinction follows from this comparison. Recommendation systems primarily answer the question of which existing product should be presented to a particular customer. Assortment policy addresses a broader economic problem – which products should remain in the portfolio, which should be expanded, and which should be reduced or removed.

Recent research on LLM-based recommendation [23; 35; 36] therefore provides an important technological component, but not a complete mechanism of assortment formation.

Mechanism for forming assortment policy based on generative AI. The central result of the study is a mechanism consisting of seven interconnected stages: data acquisition, analytical processing, generative interpretation, generation of assortment alternatives, economic evaluation, managerial validation, and feedback.

At the first stage, the enterprise consolidates the information required for assortment decisions. The proposed mechanism combines seven data groups:

– sales and transaction data;
– customer behavioural data;
– reviews, search queries, and other textual feedback;
– product attributes and category information;
– inventory indicators;
– competitor assortment information;
– market and contextual signals.

Historical sales and promotional information remain essential for demand estimation [11; 24; 25; 34]. At the same time, online behaviour can reveal consumer interest before it becomes an actual transaction. This is especially relevant in large digital catalogues, where product views, searches, and transitions between alternatives provide additional information about preferences [10; 19].

At the second stage, specialised analytical models convert these data into demand forecasts, consumer-choice patterns, profitability indicators, inventory signals, and product relationships. Generative AI is introduced only after this analytical processing.

At the third stage, the generative model interprets the combined evidence. For example, weak current sales may coexist with increasing search frequency, positive customer comments, repeated references to a missing product attribute, or limited competitive supply. In such a case, the problem cannot be interpreted adequately through historical sales alone.

At the fourth stage, GenAI generates a limited set of assortment alternatives. The proposed mechanism distinguishes five basic actions: add, retain, expand, reduce, and remove.

At the fifth stage, each alternative is evaluated according to economic and operational criteria. The main criteria are expected demand, margin contribution, inventory turnover, conversion potential, inventory feasibility, competitive position, and strategic fit.

At the sixth stage, the shortlisted alternative is validated by the responsible manager. This requirement follows from the broader literature on human-AI collaboration, which argues that AI can augment managerial decision-making without necessarily replacing human responsibility [7; 17; 27].

The final stage introduces feedback. Actual sales, profitability, customer response, and inventory dynamics after implementation become new inputs for subsequent assortment decisions.

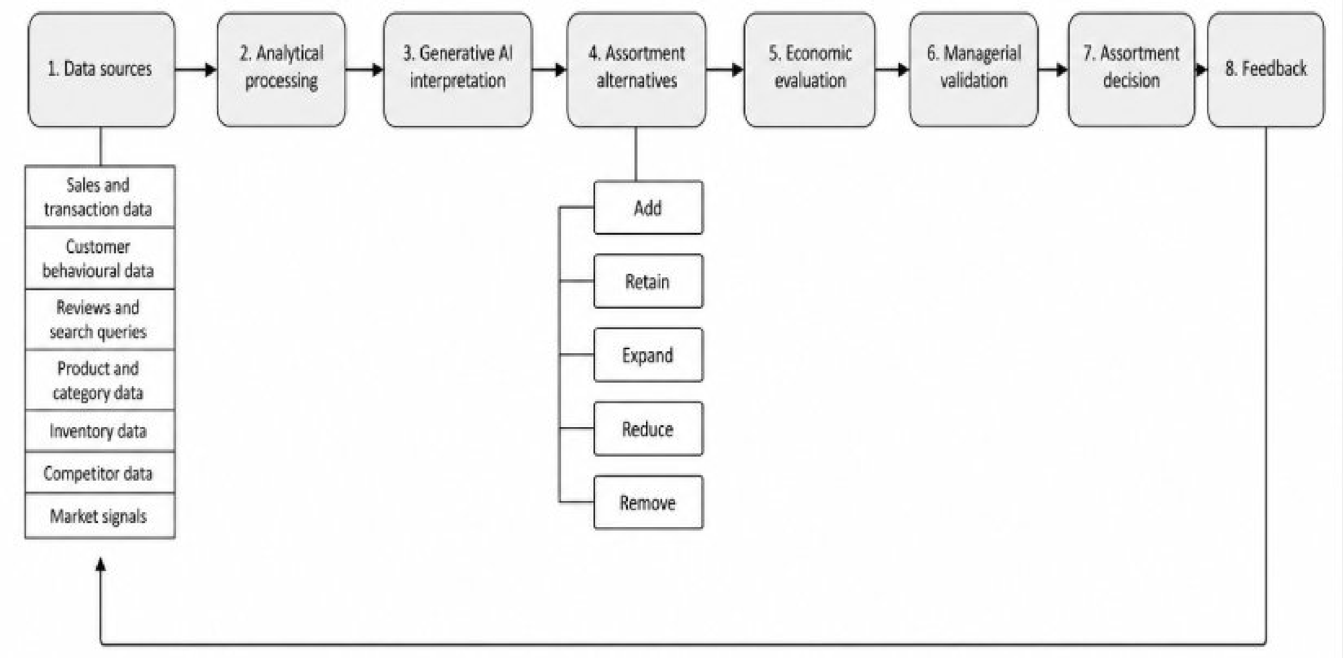

Fig. 1. Mechanism for forming the assortment policy of an e-commerce enterprise based on generative artificial intelligence

Source: developed by the author.

The mechanism therefore positions generative AI between specialised analytics and the final managerial decision. This is important because GenAI does not independently determine the economically optimal assortment. It interprets information and generates alternatives that must subsequently pass through economic and managerial controls.

Economic logic of assortment decisions. To operationalise the mechanism, the study proposes a decision matrix linking market evidence with economic conditions.

Table 2

GenAI-supported assortment decision matrix

Decision	Main evidence	Economic condition	Role of generative AI
Add	Unmet searches, emerging demand, positive semantic signals, market gap	Expected demand and margin justify introduction	Identifies unmet needs and generates product alternatives
Retain	Stable demand, acceptable margin, normal turnover	Product remains economically sustainable	Detects early changes in customer and market signals
Expand	Growing demand, stockouts, strong conversion, demand for additional variants	Expansion can increase contribution without excessive inventory risk	Identifies required attributes, variants, or complementary products
Reduce	Declining demand, weak turnover, excessive duplication	Reduction releases resources with limited loss of contribution	Identifies redundant SKUs and substitution patterns
Remove	Persistent weak demand, low profitability, excess inventory risk	Product no longer meets economic or strategic requirements	Consolidates evidence supporting discontinuation

Source: developed by the author based on [1; 13; 19; 28; 30; 31; 32].

The matrix prevents a direct transition from an AI-generated observation to an assortment decision. A product should not be added only because customer reviews are favourable, nor should it be removed solely because short-term sales have decreased. The decision must combine market evidence with profitability, turnover, inventory exposure, and category-level consequences.

This principle is particularly important for e-commerce because consumer substitution may produce misleading SKU-level signals. The removal of one product may redirect demand towards another, while excessive assortment depth may reduce inventory efficiency [30]. Similarly, the commercial value of assortment decisions should be assessed not merely through product relevance but also through their contribution to revenue and portfolio performance [31].

Managerial control, risks, and feedback. The proposed mechanism deliberately excludes fully autonomous assortment management. Generative AI can analyse large volumes of information and generate plausible explanations, but its outputs may contain unsupported or incorrect conclusions. The problem of hallucination in natural language generation is well documented [18], while recommender-system research also identifies risks related to transparency, data quality, and reliability [20].

For this reason, each GenAI-supported assortment recommendation should contain four elements:

1. the proposed action;
2. the evidence supporting the action;
3. the principal economic indicators;
4. contradictory signals or identified uncertainty.

A recommendation such as “expand this category” is therefore insufficient. The system should indicate why expansion is proposed, for example increasing search activity, repeated stockouts, favourable customer feedback, stable margins, or a detected gap in the current portfolio.

Managerial validation remains necessary because not all strategic constraints can be captured by the generative model. Supplier relationships, working-capital limits, contractual obligations, brand positioning, logistics, and the strategic role of a product category may change the final decision. The resulting decision architecture is therefore:

AI interpretation → economic evaluation → managerial validation → implementation.

This configuration corresponds to the augmentation logic identified in research on hybrid intelligence and human-AI decision-making [7; 17; 27].

The mechanism is completed by a feedback loop. After an assortment decision is implemented, the enterprise evaluates its actual effects.

Table 3

Indicators for evaluating implemented assortment decisions

Dimension	Main indicators	Purpose
Demand	Sales dynamics, category growth	Verify expected demand
Profitability	Gross margin, contribution	Evaluate economic return
Inventory	Turnover, stockouts, excess stock	Assess operational efficiency
Customer response	Conversion, search behaviour, reviews	Measure correspondence with customer needs
Portfolio efficiency	Revenue or contribution by SKU/category	Identify excessive or insufficient assortment depth
Decision quality	Difference between expected and realised effects	Improve future GenAI-supported recommendations

Source: developed by the author based on [11; 24; 25; 30; 33; 34].

The feedback stage makes the proposed mechanism adaptive. If a product introduced because of strong semantic and behavioural signals subsequently demonstrates weak conversion and low turnover, similar signals should receive more cautious interpretation in future decisions. Conversely, if emerging search queries and review themes consistently precede successful product introductions, their informational value increases.

Thus, the developed mechanism combines four functional components: an information component, which consolidates heterogeneous e-commerce data; an analytical component, which generates forecasts and measurable indicators; a generative component, which interprets signals and develops assortment alternatives; and an economic-managerial component, which evaluates, validates, implements, and subsequently reviews these alternatives.

The principal result is therefore not the replacement of conventional assortment optimisation by generative AI. Rather, the proposed mechanism integrates forecasting, customer analytics, inventory information, unstructured consumer data, LLM-based interpretation, economic evaluation, and managerial control within a single decision cycle. This makes it possible to use generative AI specifically for the formation and continuous adjustment of assortment policy while preserving the economic rationality and controllability of final decisions.

Conclusions

1. It was established that generative artificial intelligence should not replace traditional assortment optimisation, demand forecasting, or recommender systems, but should function as an interpretive decision-support layer within the assortment management process. Its principal contribution lies in combining structured and unstructured e-commerce data and transforming them into economically interpretable alternatives for assortment policy.
2. It was demonstrated that an effective mechanism for forming assortment policy in e-commerce should integrate transaction data, customer behaviour, reviews and search queries, product and category information, inventory indicators, competitor data, and broader market signals. The integration of these heterogeneous information sources makes it possible to identify not only realised demand but also unmet and emerging consumer needs that may remain invisible in conventional sales statistics.
3. It was found that the proposed mechanism should operate through a consistent sequence of stages: data acquisition, analytical processing, generative interpretation, generation of assortment alternatives, economic evaluation, managerial validation, and feedback. Within this mechanism, five principal assortment decisions were identified: add, retain, expand, reduce, and remove. These alternatives allow assortment policy to be treated as a continuous portfolio adjustment process rather than as a binary keep-or-remove decision.
4. It was confirmed that GenAI-generated assortment recommendations cannot be implemented autonomously. Each proposed action should be evaluated according to expected demand, profitability, inventory turnover, conversion potential, operational feasibility, competitive position, and strategic fit. Managerial validation remains necessary because supplier constraints, working-capital requirements, category strategy, logistics, and other organisational factors may alter the final decision. Consequently, the appropriate model is based on human-AI augmentation rather than full automation.
5. The developed mechanism should be applied as a controlled adaptive process that combines specialised analytics, generative interpretation, economic filtering, managerial approval, and subsequent performance monitoring. Its effectiveness depends on a continuous feedback loop in which actual sales, profitability, inventory dynamics, conversion, and customer response are compared with expected outcomes and used to refine subsequent assortment decisions. In this configuration, generative AI becomes an element of the economic

management system of an e-commerce enterprise rather than an isolated recommendation or content-generation tool.

Future research should focus on empirical testing of the proposed mechanism using anonymised transaction, behavioural, inventory, and customer-text data from e-commerce enterprises; comparison of different generative AI and LLM architectures; evaluation of the reliability of GenAI-supported assortment recommendations across product categories; and development of measurable decision thresholds for the automated pre-selection of add, retain, expand, reduce, and remove alternatives while preserving managerial control over final assortment decisions.

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