

Адаптивное управление персонализированным спросом на основе синергетического взаимодействия цифровых экосистем ритейла

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Аннотация. Современная парадигма потребительского спроса характеризуется переходом от индустриальной модели массового потребления к экономике индивидуальных решений. В этой связи перед розничными предприятиями встаёт задача не только прогнозировать спрос, но и обеспечивать оперативную доставку персонализированной ценности конечному потребителю в режиме реального времени. Этим обусловлена актуальность настоящей работы, направленной на преодоление разрыва между прогнозированием персонализированного спроса и его операционной реализацией. Цель исследования заключается в разработке модели адаптивного управления персонализированным спросом, синергетически объединяющей цифровые экосистемы ритейла в замкнутый цикл, в котором прогноз и реакция на него образуют единый непрерывный процесс. Для достижения поставленной цели решаются задачи выявления нерешённых проблем в области операционализации прогнозов персонализированного спроса, обоснование архитектуры адаптивного цифрового контура и включение фактора операционной жизнеспособности в систему оценки эффективности персонализации. Методологическую основу исследования составляют контент-анализ актуальных научных источников, методы имитационного моделирования поведения потребителей и нейросетевые методы обработки неструктурированных данных обратной связи. В ходе аналитического обзора выявлены две взаимосвязанные проблемы: «налог на задержку», влекущий за собой существенные финансовые потери для ритейлеров, и «парадокс гиперсегментации», при котором углубление кастомизации входит в противоречие с рентабельностью. Для преодоления данных проблем линейная модель прогнозирования, ранее разработанная автором, трансформирована в трёхмодульную адаптивную модель, объединяющую прогнозирование, интерактивное прототипирование ценности и автоматическую обратную связь. В систему оценки

эффективности дополнительно включён фактор операционной жизнеспособности, дополняющий экономические и технологические критерии. Разработанная модель обеспечивает непрерывную верификацию прогнозов и встроенный механизм отслеживания порога экономически целесообразной кастомизации.

Ключевые слова: персонализация потребления, адаптивное управление, цифровой контур ритейла, операционная жизнеспособность, синергетический подход, прогнозирование спроса

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Original article

Adaptive Management of Personalised Demand Based on Synergetic Interaction of Digital Retail Ecosystems

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Abstract. The contemporary paradigm of consumer demand is characterised by a transition from the industrial model of mass consumption to the economy of individualised solutions. In this context, retail enterprises face the challenge of not only forecasting demand but also ensuring the operational delivery of personalised value to the end consumer in real time. This determines the relevance of the present study, which is aimed at bridging the gap between the forecasting of personalised demand and its operational implementation. The aim of the research is to develop an adaptive management model for personalised demand that synergetically integrates retailers' digital ecosystems into a closed loop, where the forecast and the response are combined into a single continuous process. To achieve this aim, the following tasks are addressed: identifying unresolved problems in the operationalisation of personalised demand forecasts, substantiating the architecture of an adaptive digital circuit, and incorporating the factor of operational resilience into the system for evaluating personalisation effectiveness. The methodological basis of the study comprises content analysis of current academic sources, simulation modelling of consumer behaviour, and neural network methods for processing unstructured feedback data. The analytical review identified two interrelated problems: the "delay

tax", which entails substantial financial losses for retailers, and the "hypersegmentation paradox", in which the deepening customisation comes into conflict with profitability. To overcome these problems, the linear forecasting model previously developed by the author has been transformed into a three-module adaptive model that combines forecasting, interactive value prototyping, and automated feedback. The operational viability factor, which supplements economic and technological criteria, has additionally been introduced into the performance evaluation system. The developed model ensures continuous verification of forecasts and incorporates an embedded mechanism for tracking the threshold of economically viable customisation.

Keywords: personalisation of consumption, adaptive management, digital retail loop, operational viability, synergetic approach, demand forecasting

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Introduction

The relevance of this study is determined by the logic of scientific inquiry established during the preceding stage of analysing the contemporary paradigm of consumer demand. In the previously conducted research, a scientific and methodological approach to demand forecasting was developed, taking into account the regional factors of the Donetsk People's Republic, and a synergetic approach to evaluating the effectiveness of personalisation as an exclusive value matrix was substantiated [4]. However, as practice has demonstrated, creating an accurate forecast and confirming its effectiveness at the planning stage is insufficient. The stage of practical integration of the personalisation mechanism into the fabric of retail operations emerges as the key challenge.

The trajectory of movement from mass consumption to the economy of individualised solutions demands a rethinking not only of the customer interaction interface but of the entire back-end architecture of the enterprise. If one operates with static datasets and trends at the forecasting stage, then, at the implementation stage, the task arises of creating an adaptive digital loop capable of finding, in real time, an equilibrium between the depth of customisation and the stability of the system.

Contemporary retail is undergoing a phase of large-scale systemic restructuring driven by the convergence of digital technologies, the transformation of consumer expectations, and the infusion of artificial intelligence into operational processes [7]. Researchers identify a fundamental shift: competition is migrating from the size of retail chains and physical floor space to the quality of data management, demand management and customer attention [9]. According to forecasts, the global AI in retail

market will reach 164.74 billion dollars by 2030, with 76% of retailers already increasing investments in this domain [6]. Under these conditions, personalisation ceases to be a competitive advantage and becomes a baseline standard of consumer interaction [11].

The academic community is actively developing the toolkit that provides the technological foundation for hyper-personalisation. Researchers define it as the use of real-time data to deliver a relevant offer to a specific user in a specific context [14]. The deployment of such systems demonstrates measurable economic effects: companies that have rolled out AI-powered personalisation report increased conversion rates, higher average transaction values and improved customer retention¹. Macy's, implementing a personalisation strategy powered by Adobe AI, transitioned from a transactional model to a relational one, where the homepage content dynamically adapts to the individual interests of each visitor. The experience of the Foxtrot chain is illustrative: the introduction of a transformer-based product recommendation model enhanced by large language models made it possible to analyse the sequence of customer actions in real time and to generate contextually meaningful offers².

In the academic sphere, Liu X. and Chen X. proposed a hierarchical Bayesian model for identifying behavioural consumer segments based on transactional data, supplemented with LLM-based interpretation [2]. Shahbazi Z., Jalali R., and Shahbazi Z. developed a cross-domain adaptive recommendation system capable of dynamically adjusting to shifts in user interests [10]. Progress has been achieved in sales forecasting: the application of MLP regressors and RFM analysis enables the simultaneous resolution of demand forecasting and customer segmentation tasks, with R^2 values reaching 0.94. Russian retail chains are also investing in technological re-equipment: X5 Group has migrated inventory management to its proprietary platform, Magnit has automated the analysis of up to 150,000 customer reviews per day, and Lenta has introduced machine-learning-based demand forecasting [12].

Parallel to technological progress, researchers are identifying an important behavioural trend: the paradox of abundance, whereby excessive choice blocks purchase decision-making. Experiments have shown that reducing assortment within a category by 60% can increase conversion by 12% [11]. Consumers increasingly visit offline stores for a specific, pre-determined purchase: 73% of shoppers check prices and product availability online beforehand and are guided by speed and convenience when at the physical point of sale³. This corroborates the thesis of a transition to the economy

¹ Giperpersonalizatsiya v marketinge: kak prevzoyti ozhidaniya [Hyper-personalization in marketing: how to exceed expectations] // CleverData. URL: <https://cleverdata.ru/blog/statii/giperpersonalizatsiya-v-marketinge> (accessed: 09.05.2026). (In Russian).

² How Macy's is reinventing retail with AI-powered personalization // Adobe UK. URL: <https://business.adobe.com/uk/blog/macys-reinventing-retail-with-ai-powered-personalization> (accessed: 09.05.2026).

³ Future of the store // Deloitte. <https://www2.deloitte.com/global/en/pages/consumer-business/articles/future-of-retail.html> (accessed: 09.05.2026).

of individualised solutions, where value is shaped not by breadth of assortment but by relevance to a specific buyer at a specific moment.

However, amidst the diversity of technological solutions, a critical gap emerges in the literature: the question of what happens after a personalised demand forecast has been generated remains insufficiently explored. A study conducted by Anaplan, Incisiv, and the World Retail Congress introduces the concept of the latency tax — the aggregate financial losses arising from the gap between the moment a market signal changes and the moment inventories, supplies, or prices are adjusted in response to that change.

According to the findings, slow decision-making costs retailers an average of five cents for every dollar of revenue. Key sources of loss include measurement latency (two-thirds of retailers update forecasts no more than once a month), decision latency (three-quarters rely on manual signal processing), and execution latency (nearly 70% update inventories monthly)⁴. Market leaders, by contrast, update forecasts weekly or more frequently, actively deploy automated decision-making, and reduce latency losses to two cents per dollar [8]. In other words, the problem lies not in forecast accuracy per se, but in the speed of its operationalisation.

As personalisation deepens, a second, under-researched phenomenon emerges: the hypersegmentation paradox. The drive towards maximum offer customisation aligned with individual value matrices comes into conflict with the economic efficiency of operational processes. The atomisation of demand provokes rising costs in logistics, assortment management, and marketing, calling into question the very feasibility of extremely deep personalisation [15]. In existing literature, this paradox has not been conceptualised and lacks a methodological solution.

The ethical dimension of hyper-personalisation, which is acquiring institutional resonance, deserves separate attention. Research documents that personalisation is increasingly becoming an instrument of price discrimination: dynamic pricing algorithms enable different prices to be offered to different buyers for the same product [6, 14].

This engenders a problem of consumer trust. More than two-thirds of shoppers believe that too much is demanded of them in exchange for advantageous offers. Alvarez & Marsal experts note that in grocery retail, dynamic pricing requires particular caution: non-transparent pricing logic can provoke reputational risks. In the United States, regulators are already demanding disclosure of the use of pricing algorithms at the level of the individual consumer, while Romania is preparing a ban on dynamic pricing in retail⁵. In the same context, the Federal Antimonopoly Service of Russia has

⁴ The latency tax: avoiding the cost of delayed retail decisions // Anaplan Blog. URL: <https://www.anaplan.com/blog/latency-tax-avoiding-cost-delayed-retail-decisions/> (accessed: 09.05.2026).

⁵ Unlocking the next frontier of personalized marketing // McKinsey & Company : [site]. URL: <https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/unlocking-the-next-frontier-of-personalized-marketing> (accessed: 09.05.2026).

launched an inquiry into commission mechanisms and ranking algorithms on marketplaces, effectively examining the architecture of demand distribution within platforms⁶.

Despite significant progress in the development of forecasting technologies, recommendation systems and dynamic pricing, the existing body of research is characterised by fragmentation: predictive models, operational management and the ethical-regulatory aspects of personalisation are examined in isolation [7, 1].

Thus, the unresolved problem that has defined the conception of the present article is the absence of a scientifically grounded mechanism for transitioning from predictive models of personalised demand to adaptive operational management, capable of simultaneously bridging the temporal gap between forecast and action, identified as the latency tax; preventing the collapse of profitability as customisation deepens the hypersegmentation paradox [7]; and ensuring the transparency and ethicality of algorithmic decisions in alignment with emerging regulatory requirements [6, 13, 14].

The subject of the research is the architecture of an adaptive digital loop of a retail enterprise, integrating forecasting, interactive value testing and self-learning feedback into a single closed cycle.

The aim of the article is to develop an adaptive management model for personalised demand that ensures the synergetic interaction of digital retail ecosystems and minimises the operational gap between forecast exclusive value and actual consumer satisfaction⁷.

Methodology and Research Methods

The study rests on a three-component methodology:

- 1) content analysis of the results of implementing predictive models previously developed by the author [3, 4];
- 2) agent-based simulation modelling methods;
- 3) neural network methods for processing unstructured feedback data [10].

Retail enterprises with a level of data maturity sufficient to enable the validation and adjustment of forecasts serve as the testing ground. The research design envisages a transition from the cascaded “Data Collection — Forecast” model to the adaptive “Forecast — Interaction — Self-Learning” model.

⁶ Shopper & Category Management. Signaly 2026: sistemnaya perestroyka riteyla [Shopper & Category Management. Signals 2026: systemic restructuring of retail] // RBC Companies. URL: <https://companies.rbc.ru/news/9T-D0qPDion/shopper-and-category-management-signalyi-2026-sistemnaya-perestrojka-ritejla/> (accessed: 09.05.2026). (In Russian).

⁷ Giperpersonalizatsiya kak faktor tsenovoy diskriminatsii: kak media i e-commerce ispol'zuyut dannye dlya raznykh tsen na kontent i reklamu? [Hyper-personalization as a factor of price discrimination: how media and e-commerce use data for different prices on content and advertising?] // Financial University under the Government of the Russian Federation : [site]. URL: <https://www.fa.ru/university/structure/university/uso/press-service/press-releases/giperpersonalizatsiya-kak-faktor-tsenovoy-diskriminatsii-kak-media-i-e-commerce-ispolzuyut-dannye-dl> (accessed: 09.05.2026). (In Russian).

The Architecture of the Adaptive Digital Loop and the Rationale for Its Necessity

Continuing the line of analysis associated with the formation of exclusive value matrices for each consumer, we encounter an economic constraint. The rethinking of traditional value-creation mechanisms noted in our earlier work [4], when absolutised, leads to a situation in which endless offer diversification ceases to generate additional value. We designate this as the hypersegmentation paradox: the point at which the incremental satisfaction gained through personalisation is neutralised by the exponential growth of transaction costs required to sustain the uniqueness of the logistics, warehousing, and advertising mix [15].

When we discuss the introduction of personalisation in retail, two groups of factors almost always lie on the surface and are typically evaluated first. These are economic indicators — such as growth in average transaction value, increased conversion rates, enhanced customer lifetime value — and technological indicators: the accuracy of recommendation algorithms, data processing speed and the throughput of digital infrastructure [2, 12]. It is upon these that the overwhelming majority of studies concentrate, and it is these that businesses habitually embed in investment justifications. Yet practical experience demonstrates that a system built solely on these two pillars resembles a building with a splendid façade and expensive finishes but lacking the load-bearing walls capable of withstanding a hurricane. Economics and technology answer the question “How much will we earn and how quickly will we do it?” but they leave unanswered another, no less important question: “What will happen to the system when conditions change abruptly, and will it be able not merely to endure but to preserve its functionality and purpose in a new reality?”

It is precisely this gap that the factor we are introducing into the personalisation effectiveness evaluation framework — the factor of operational resilience — is intended to close. What is meant here is not stability in the static, engineering sense, where a structure simply resists external pressure, but a far more complex and organic property: the capacity of the entire personalised ecosystem of an enterprise to adapt to disturbances without losing its identity and without a catastrophic decline in the quality of consumer interaction [5, 8].

To understand why this factor becomes decisive, it suffices to imagine the context in which contemporary retail chains operate, particularly in regions with complex and fluid institutional environments [4, 9]. Today, an offer shaped for a specific buyer rests upon dozens of interconnected processes: logistics chains, warehouse inventories, pricing algorithms, digital storefronts, communication channels. All of these are calibrated to a particular forecast scenario. But what happens when this scenario ceases to correspond to reality — for instance, due to a sudden supply disruption, exchange rate fluctuations, a shift in the population’s payment behaviour or even weather anomalies that abruptly redirect demand towards an unexpected product category? If the system is designed without accounting for operational resilience, it either continues to blindly

follow the outdated forecast, generating irrelevant offers and losing customer trust, or it collapses in an attempt to recalculate thousands of parameters instantaneously, spawning chaos in procurement and communications [8].

Operational resilience, as we understand it, is the property of a system to preserve the coherence and meaningfulness of personalised offerings even when the predictive model temporarily loses accuracy due to an external shock. It is the ability not merely to switch to a backup plan but to smoothly, without jolts or ruptures, redistribute the load, reformat assortment priorities and adjust the tone of communication with the buyer so that the latter either does not notice the turbulence at all or perceives the brand's reaction as natural, caring and appropriate. Incorporating this factor into a unified evaluation framework alongside economic and technological criteria means that we cease measuring personalisation effectiveness exclusively in terms of profit and speed and begin to evaluate its maturity. A mature system is not one that delivers maximum margin under ideal conditions but one that continues to do so creditably under fundamentally non-ideal conditions, preserving both profitability and consumer loyalty [5, 8].

Thus, by integrating the factor of operational resilience into our synergetic approach, we seek to move beyond a flat, two-dimensional picture in which everything reduces to the dichotomy of “technology versus money”. We add a third dimension that renders evaluation three-dimensional and closer to real life. The economic factor tells us about the commercial attractiveness of personalisation, the technological factor about its feasibility and the operational resilience factor about its long-term viability — about how sturdy the bridge between forecast exclusive value and actual consumer satisfaction will prove to be when the elements of the real market strike that bridge [4, 5]. It is precisely this three-dimensional vision, in our view, that ensures the qualitatively new level of interaction between the retail enterprise and the consumer (Fig. 1).

The architecture of the developed model represents a closed three-module loop operating in a continuous regime. The starting point is Module I — Forecasting, in which a primary demand forecast is formed on the basis of streaming data collection, trend identification and the integration of dynamic regional and institutional factors [6]. Unlike traditional linear logic, the forecast is not transmitted directly to operational planning but passes to Module II — Interactive Value Prototyping. Here, algorithms generate a “value cloud” — a collection of virtual micro-offers and digital twins of products that are fanned out to consumers via digital interaction channels [10].

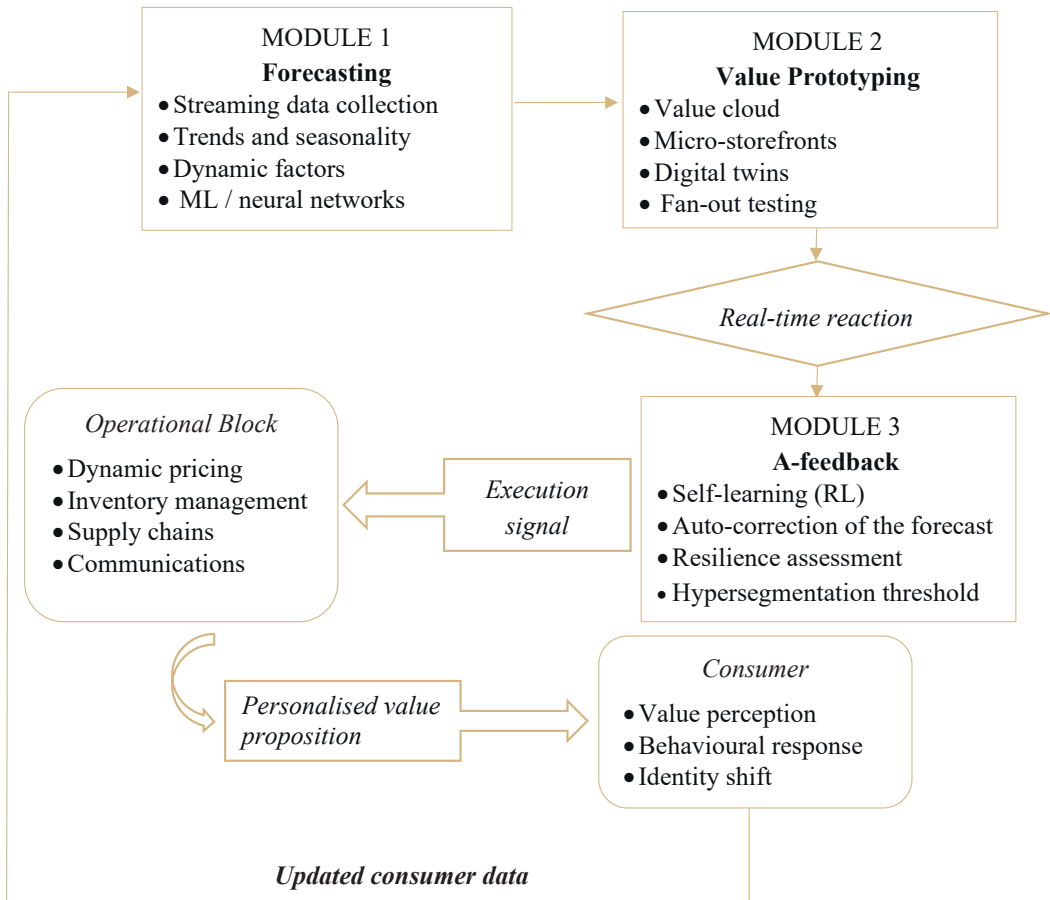


Fig. 1. An Adaptive Management Model for Personalised Consumer Demand

Source: compiled by the author.

Reactions to these offers — clicks, biometric responses, behavioural patterns — are analysed in real time by Module III — A-Feedback. This module, based on reinforcement learning, adjusts the predictive model without expert intervention, monitors the system’s operational resilience and manages the hypersegmentation threshold [2, 10]. Following correction, the signal proceeds to the operational block — dynamic pricing, inventory management and communications — while the consumer’s digital footprint closes the loop, returning to Module I as updated data⁸. Thus, the architecture implements the “Forecast — Interaction — Self-Learning” principle with zero temporal gap.

⁸ How agentic AI is changing the way people shop // Okoone. URL: <https://www.okoone.com/spark/industry-insights/how-agentic-ai-is-changing-the-way-people-shop/> (accessed: 09.05.2026).

The transition from forecasting to the operational management of personalised demand requires an answer to one fundamental question: “What happens to a forecast after it has been deemed reliable?” The logic of our previous study [4] led to the point at which the scientific-methodological apparatus considered its task fulfilled — the predictive model was verified by experts, the figures aligned and regional specificity was accounted for. Yet beyond this point, in the actual realm of retail operations, a phenomenon emerges that radically changes the perception of the sufficiency of even the most accurate forecast.

Let us imagine an enterprise that has exemplarily completed all five stages of the chain we proposed earlier: data have been collected and systematised, trends and seasonal fluctuations identified, dynamic factors integrated into the model and the final forecast subjected to validation and expert adjustment [4]. On paper and in analytical dashboards, an ideal picture is presented, confirming the soundness of the method. However, at the very moment this forecast is handed over for execution — into procurement, logistics, the formation of personalised offers — a gap materialises in the real world. And this gap lies not in the quality of the forecast but in the very nature of the time in which it exists.

A forecast, however accurate, always remains a snapshot of the past formatted for the future. It captures the state of consumer identity at the moment of the last analytical iteration. But in a paradigm where every product becomes a reflection of personal identity, that identity itself does not wait for the next scheduled forecasting cycle. It shifts continuously — under the influence of the information field, social interactions and emotional impulses⁹. By the time the forecast is transformed into a product offer on a shelf or in a digital storefront, the consumer for whom all of this was intended may already be situated at a different value point. Expert adjustment, tied to the human rather than to the flow, fundamentally cannot keep pace — not due to a lack of qualifications but owing to the fundamental limitation of linear architecture.

It is precisely this chronological gap — between the time of forecasting and the time of consumption — that constitutes the nexus compelling a reconsideration of the approach’s architecture. If personalisation genuinely aspires to serve as an exclusive value matrix for each buyer, then the methodology cannot rest at prediction. It must enter into the very process of interaction with the consumer, becoming part of that process rather than a stage preceding it. Recognition of this gap and its economic consequences serves as the point of departure for the transition to the concept of the adaptive digital loop.

We propose not to dismantle the previous model but to transform it from a straight line into a closed loop with zero response time. We “recode” the logical chain so that it ceases to be cascaded. Instead of concluding the process with the “expert —

⁹ How agentic AI is changing the way people shop // Okoone. URL: <https://www.okoone.com/spark/industry-insights/how-agentic-ai-is-changing-the-way-people-shop/> (accessed: 09.05.2026).

validation — correction” stage, we introduce two new functional modules that together constitute the essence of the adaptive loop architecture.

The first module is interactive value prototyping. As soon as the primary digital forecast has been generated, it is not sent to the procurement department as a directive. Instead, the system instantaneously generates a “value cloud” — a set of virtual yet functional micro-offers, personalised storefronts or digital twins of products [10]. These offers are fanned out via digital interaction channels in fractions of a second to target segments or even to specific consumers. This is neither a survey nor a focus group; it is gentle, unobtrusive testing of real choice and emotional response at a moment close to the decision-making point¹⁰. We do not wait for an expert to compare the forecast with last week’s reports — we allow the market itself, in real time, to confirm or delicately adjust our forecast.

The second module is automated feedback, or A-Feedback. Here we transition from adjustment mediated by human consciousness and experience to the self-tuning of the system. The digital footprint and streaming data on reactions to the value cloud are analysed by algorithms continuously. The system learns not from historical transactions but from live behaviour, from how consumer identity manifests itself at this very second [2, 10]. This is of fundamental importance for a complex environment such as the economy of the Donetsk People’s Republic, where the high level of uncertainty and dynamic institutional factors render any delayed expert assessments too slow for successful personalisation [4, 9]. The adaptive loop, by contrast, allows not merely to describe demand but to assist in its formation, capturing the slightest fluctuations of identity and transforming them into tactical offers without a temporal gap and without the accumulation of erroneous forecast hypotheses.

Thus, the reformatting of the approach is not complication for the sake of complication. It is an evolutionary response to a new paradigm in which value has ceased to be a static characteristic of a product and has become a living, breathing dialogue with the consumer [4, 11]. The adaptive loop constitutes the architectural foundation of such a dialogue.

Conclusion

The conducted study was governed by an overarching logic linking the forecasting of personalised demand to the operational reality of the retail enterprise, and its results naturally coalesce around the central conception: the development of an adaptive management model capable of bridging the gap between predicted exclusive value and its actual delivery to the consumer.

¹⁰ How agentic AI is changing the way people shop // Okoone. URL: <https://www.okoone.com/spark/industry-insights/how-agentic-ai-is-changing-the-way-people-shop/> (accessed: 09.05.2026).

An analytical review of current scholarly sources confirmed that the research landscape in the domain of personalisation is undergoing a phase of vigorous yet fragmented growth. On the one hand, impressive progress has been achieved in the development of recommendation systems, predictive demand models and dynamic pricing — companies and academic teams demonstrate high forecasting accuracy and deploy transformer architectures based on large language models. On the other hand, a critical gap emerges within this body of work: there is a virtual absence of studies devoted to what happens after a forecast has been generated. Content analysis enabled the conceptualisation of two interrelated problems that have not previously received systematic treatment. The first is the aggregate financial losses arising from the temporal gap between a change in the market signal and the moment of operational decision adjustment; empirical data indicate that these losses cost retailers an average of five cents for every dollar of revenue. The second problem is the hypersegmentation paradox, whereby the drive towards infinitely deep customisation enters into contradiction with the profitability of operational processes. It is precisely these two unresolved problems that defined the subject and purpose of the present work.

In response to the identified gap, the study substantiates the necessity of reformatting the scientific-methodological approach to consumer demand forecasting previously proposed by the author. Whereas in the preceding model the logical chain concluded with the stages of validation and expert adjustment, it has now been transformed into a closed adaptive loop comprising three modules: forecasting, interactive value prototyping and automated feedback. The fundamental distinction of the proposed architecture lies in the fact that the forecast ceases to be a final product handed over to operational planning and becomes a hypothesis undergoing continuous verification through real-time interaction with the consumer. The interactive prototyping module generates a value cloud — a collection of virtual micro-offers that are tested on target segments without directive dispatch to procurement — while the A-Feedback module, based on reinforcement learning, adjusts the model without expert intervention, ensuring zero time lag between the market signal and the system's response.

A significant contribution to the development of the synergetic approach laid down by the author at the previous stage of the research is the introduction of the factor of operational resilience into the personalisation effectiveness evaluation framework. The traditional two-dimensional coordinate system, operating solely with economic and technological indicators, has proven insufficient to describe the behaviour of a personalised ecosystem in an unstable institutional environment. The economic factor answers the question of the commercial attractiveness of personalisation, the technological factor of its feasibility, but only operational resilience makes it possible to judge the system's viability in the long term, when external shocks — from supply chain disruptions to abrupt shifts in payment behaviour — call into question the relevance of any forecast, however accurate. A mature personalised system, in this understanding, is not one that delivers maximum margin under ideal conditions but one that preserves both profitability and consumer loyalty under fundamentally non-ideal

conditions, smoothly redistributing the load and adjusting the tone of communication so that the buyer either does not notice the turbulence at all or perceives the brand's reaction as natural and caring.

Thus, the developed adaptive management model for personalised demand enables the resolution of the stated scientific task: it ensures the synergetic interaction of digital retail ecosystems and minimises the operational gap between forecast exclusive value and actual consumer satisfaction. The model simultaneously addresses both the latency tax — through the closure of the loop and the abandonment of discrete forecasting cycles — and the hypersegmentation paradox — through the embedded mechanism for tracking the threshold beyond which further customisation ceases to be profitable.

The further research trajectory is seen in studying the ethical dimension of identity prediction — the moment when adaptive algorithms begin not so much to reflect consumer behaviour as to shape it, and when the question of the permissible limits of influence on consumer choice arises.

References

1. Consumers and artificial intelligence: an experiential perspective / S. Puntoni, R. W. Reczek, M. Giesler, S. Botti // *Journal of Marketing*. 2020. Vol. 85, no. 1. P. 131–151. doi:10.1177/0022242920953847.
2. Customer experiences in the age of artificial intelligence / N. Ameen, A. Tarhini, A. Reppel, A. Anand // *Computers in Human Behavior*. 2021. Vol. 114. doi:10.1016/j.chb.2020.106548.
3. Donets L. I. Ekosistemnyy podkhod k predprinimatel'skoy deyatel'nosti v sfere roznichnoy trgovli [Ecosystem approach to entrepreneurial activity in the retail sector] // *Fundamental'nye issledovaniya [Fundamental Research]*. 2025. No. 1. P. 99–103. doi:10.17513/fr.43770. (In Russian).
4. Donets L. I. Personalizatsiya v sisteme sovremennoy paradigmy potrebitel'skogo sprosa [Personalisation in the system of the modern consumer demand paradigm] // *Fundamental'nye issledovaniya [Fundamental Research]*. 2025. No. 9. P. 21–27. doi:10.17513/fr.43897. (In Russian).
5. Donets L. I. Tsifrovaya transformatsiya potrebitel'skogo povedeniya: integrirovanny podkhod k issledovaniyu [Digital transformation of consumer behaviour: an integrated approach to research] // *Vestnik Rossiyskogo ekonomicheskogo universiteta imeni G. V. Plekhanova [Bulletin of the Plekhanov Russian University of Economics]*. 2026. Vol. 23, no. 2(146). P. 103–113. doi:10.21686/2413-2829-2026-2-103-113. (In Russian).
6. Global reconstruction of language models with linguistic rules — Explainable AI for online consumer reviews / M. Binder, B. Heinrich, M. Hopf, A. Schiller // *Electronic Markets*. 2022. Vol. 32. P. 2123–2138. doi:10.1007/s12525-022-00612-5.
7. Huang M-H., Rust R. T. A strategic framework for artificial intelligence in marketing // *Journal of the Academy of Marketing Science*. 2021. Vol. 49. P. 30–50. doi:10.1007/s11747-020-00749-9.
8. Rajagopal R., Sharma R. Supply chain resilience: A review, conceptual framework and future research // *The International Journal of Logistics Management*. 2021. Vol. 34, no. 4. P. 879–908. doi:10.1108/IJLM-03-2021-0169.

9. Rodnikova O.Yu., Charakha Ber A.R. Tsifrovaya ekonomika i tsifrovaya transformatsiya: osobennosti mirovykh strukturnykh protsessov [Digital economy and digital transformation: features of global structural processes] // *Mezhdunarodnaya trgovlya i trgovaya politika* [International Trade and Trade Policy]. 2024. Vol. 10, no. 4. P. 104–113. doi:10.21686/2410-7395-2024-4-104-113. (In Russian).
10. Shahbazi Z., Jalali R., Shahbazi Z. Enhancing recommendation systems with real-time adaptive learning and multi-domain knowledge graphs // *Big Data and Cognitive Computing*. 2025. Vol. 9, no. 5. doi:10.3390/bdcc9050124.
11. Smirnova M. M., Staroverova I. I. Strategii postanovki tseley v upravlenii brendom i loyal'nost'yu klienta v usloviyakh ekonomicheskoy transformatsii [Strategies for goal setting in brand management and customer loyalty under economic transformation] // *Marketingovye strategii i praktiki* [Marketing Strategies and Practices]. 2025. Vol. 16, no. 2. P. 100–117. doi:10.29141/2218-5003-2025-16-2-7. (In Russian).
12. Tang J. Unlocking retail insights: predictive modeling and customer segmentation through data analytics // *Journal of Theoretical and Applied Electronic Commerce Research*. 2025. Vol. 20, no. 2. Article 59. doi:10.3390/jtaer20020059.
13. Technology-enabled personalization in retail stores: understanding drivers and barriers / A. S. Riegger, J. F. Klein, K. Merfeld, S. Henkel // *Journal of Business Research*. 2021. Vol. 123. P. 140–155. doi:10.1016/j.jbusres.2020.09.039.
14. The Impact of AI-Generated Marketing Content on Consumer Behavior / T. -H. Afrin, A. Ahmed, M. L. A. Banu, A. Banu // *International Journal of Multidisciplinary Research and Analysis*. 2026. Vol. 9. P. 3793–3803. doi:10.47191/ijmra/v9-i6-60.
15. Tkach D. N. Sovremennye tendentsii i ikh vliyanie na razvitie sfery riteyla [Modern trends and their impact on retail development] // *Journal of Monetary Economics and Management*. 2024. No. 10. doi:10.26118/2782-4586.2024.70.43.096. (In Russian).

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