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ORGANIZATIONAL AND ECONOMIC MECHANISMS FOR ENHANCING THE EFFICIENCY OF RETAIL SERVICES THROUGH ARTIFICIAL INTELLIGENCE TECHNOLOGIES

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Abstract. This article examines the organizational and economic mechanisms through which artificial intelligence (AI) enhances service efficiency in retail trade enterprises. The relevance of the topic is driven by intensifying competition, changing consumer expectations, and the rapid development of the digital economy in Uzbekistan under the national Strategy for the Development of Artificial Intelligence Technologies until 2030. The aim of the study is to assess the impact of AI adoption on retail service efficiency and to substantiate the mechanisms that convert this adoption into measurable performance gains. A mixed-methods design was applied: a survey of 128 retail enterprises operating in different regions of Uzbekistan, semi-structured interviews with 17 industry experts, and analysis of official statistical data. Service efficiency was measured through an integral coefficient combining speed, accuracy, availability, cost, and customer satisfaction. The results show that enterprises applying AI solutions in an integrated manner reduced average customer service time by 41 per cent, increased order fulfilment accuracy by 17 per cent, raised the customer satisfaction index by 24 per cent, and lowered operating costs by 21 per cent. Correlation analysis confirmed a strong positive relationship between the intensity of AI adoption and service efficiency ($r = 0.58$–0.74). The study also identifies key barriers such as digital-skills shortages, high integration costs, and data-security concerns. On this basis, a phased implementation model and a set of organizational and economic mechanisms are proposed. The findings are useful for retail managers, sector regulators, and researchers of the digital economy.

Keywords: artificial intelligence; retail trade; service efficiency; digital transformation; machine learning; customer experience; organizational mechanisms; economic mechanisms; personalization; Uzbekistan.

INTRODUCTION

In the third decade of the twenty-first century, artificial intelligence has become one of the principal drivers of transformation in the global economy. Technologies such as machine learning, natural language processing, computer vision, and predictive analytics are reshaping business models, value chains, and, above all, the ways in which enterprises interact with their customers. Retail trade, as a sector that operates at the immediate point of contact between supply and demand, is particularly sensitive to these changes: the speed, accuracy, and personalization of service increasingly determine competitiveness more than price or assortment alone.

The pressure on retail enterprises has grown sharply with the expansion of electronic commerce and the rise of consumers who expect instant, seamless, and individualized service across physical and digital channels. In this environment, the efficiency of service — understood as the ratio between the quality and speed of customer service and the resources expended to deliver it — has become a strategic priority. Artificial intelligence offers retailers a powerful set of instruments to raise this efficiency by automating routine operations, forecasting demand, personalizing offers, and supporting managerial decision-making with data.

For Uzbekistan, these questions are especially timely. The country is pursuing an ambitious digital agenda: the "Digital Uzbekistan – 2030" strategy laid the foundations of the digital economy, and the "Strategy for the Development of Artificial Intelligence Technologies until 2030", approved by Presidential Resolution No. RP-358 of 14 October 2024, set concrete targets, including expanding the volume of AI-based products and services to 1.5 billion US dollars and entering the top fifty countries of the Government AI Readiness Index. These policy commitments create a favourable environment for retail enterprises to adopt AI, but they also raise a practical question that remains insufficiently studied: through which organizational and economic mechanisms does AI adoption translate into real improvements in service efficiency?

The significance of these questions is heightened by the economic weight of the retail sector itself. Retail trade is one of the largest employers and a major contributor to value added in most economies, and it functions as the final link that connects national production and imports with household consumption. Because the sector is characterized by thin margins, high transaction volumes, and direct daily contact with large numbers of customers, even modest improvements in the efficiency of service can produce considerable aggregate effects on costs, revenues, and consumer welfare. At the same time, retail is undergoing a profound behavioural shift: consumers increasingly move fluidly between offline and online channels, compare offers instantly, and expect service to be both fast and personal. Artificial intelligence is one of the few instruments capable of reconciling these competing demands at scale, which is why its role in retail service deserves systematic study.

The scientific problem addressed in this article lies precisely in this gap. Much of the existing research demonstrates that AI can improve individual service indicators, yet it rarely explains, in a systematic way, the organizational and economic mechanisms that link technology adoption to sustainable efficiency gains, particularly in the context of emerging economies. The aim of the research is to identify, substantiate, and empirically assess these mechanisms in retail trade enterprises. The objectives are: to analyse the theoretical foundations of AI-driven service efficiency; to measure the effect of AI adoption on key efficiency indicators; to reveal the mechanisms that mediate this effect; and to develop practical recommendations. The object of the study is the process of service delivery in retail trade enterprises, while the subject is the organizational and economic mechanisms of enhancing service efficiency through AI. The central hypothesis is that the integrated application of AI technologies, supported by adequate organizational capabilities, produces a statistically significant improvement in retail service efficiency. The scientific novelty consists in a joint organizational-and-economic treatment of these mechanisms and in their empirical grounding on data from retail enterprises in Uzbekistan.

LITERATURE REVIEW

The efficiency of services has long been a central theme in the management and marketing literature. The service-dominant logic proposed by Vargo and Lusch [1] reframed value as something co-created in the interaction between the enterprise and the customer, shifting attention from tangible products to the quality of service processes. Within this tradition, the SERVQUAL model of Parasuraman, Zeithaml, and Berry [2] established a durable framework for assessing service quality along the dimensions of reliability, responsiveness, assurance, empathy, and tangibles — dimensions that remain highly relevant when service is mediated by intelligent technologies. Rust and Huang [3] argued that advances in technology inevitably enlarge the service sector and raise its optimal productivity, anticipating the current wave of automation.

The theoretical understanding of AI in service was substantially advanced by Huang and Rust [4], who proposed a theory of AI job replacement based on four types of intelligence required for service tasks — mechanical, analytical, intuitive, and empathetic. Their framework clarifies which service tasks are most readily augmented or automated by AI and which continue to depend on human capabilities, and it provides a conceptual basis for allocating tasks between humans and machines. In later work, Huang and Rust [5] extended this reasoning into a strategic framework for using different forms of AI to engage customers, emphasizing that the value of AI in service depends on aligning the technology with the nature of the task and the stage of the customer relationship.

A parallel stream of research has focused specifically on retailing. Shankar [6] showed how AI is reshaping retail across the entire value chain, from assortment planning and pricing to fulfilment and customer service. Grewal, Roggeveen, and Nordfält [7] identified the technological forces transforming the future of retailing and stressed the growing role of data and automation in shaping the customer experience. Davenport, Guha, Grewal, and Bressgott [8] provided an influential analysis of how AI will change marketing and retailing, distinguishing between task automation, cognitive insight, and cognitive engagement, and highlighting the organizational conditions required to capture value from AI. Building on this work, Shankar, Kalyanam, and colleagues [18] mapped how a wide range of technologies, including AI, is reshaping retail formats, operations, and the customer interface, while Grewal, Hulland, Kopalle, and Karahanna [17] argued more broadly that technology is transforming marketing across multiple domains and called for integrative research linking technological change to organizational and economic outcomes.

A more specialized line of inquiry has addressed personalization, one of the most visible service applications of AI in retail. Kumar, Rajan, Venkatesan, and Lecinski [19] analysed how AI enables personalized engagement marketing by predicting individual preferences and tailoring interactions at scale, thereby improving both customer satisfaction and firm profitability. Kietzmann, Paschen, and Treen [16] examined how AI supports marketers along the consumer journey, from awareness to post-purchase service, while Wirth [20] emphasized that the practical value of AI depends on the availability of high-quality data and clearly defined business objectives. These studies indicate that personalization is not merely a technical feature but a mechanism linking data-driven capabilities to measurable service outcomes, provided that the enterprise possesses the organizational conditions to exploit it.

The mechanisms connecting technology to performance have been examined within the broader literature on digital transformation. Vial [9] synthesized this field and showed that digital transformation is not merely a technological phenomenon but a process that reconfigures organizational structures, capabilities, and value creation. Verhoef and colleagues [10] similarly argued that digital transformation requires new organizational forms, resources, and metrics, while Bharadwaj, El Sawy, Pavlou, and Venkatraman [11] emphasized that a digital business strategy must be fused with organizational capabilities to generate competitive advantage. Brynjolfsson and McElheran [12] provided empirical evidence that data-driven decision-making raises productivity, offering a direct link between analytical capability and economic performance.

Although the international literature on AI in retail is expanding rapidly, evidence from emerging economies remains comparatively limited. National and international policy analyses, including the OECD review of AI readiness [23] and the assessments accompanying Uzbekistan's AI strategy [21], [22], indicate that developing countries are moving from experimentation to institutionalized adoption, but that they face specific constraints related to skills, infrastructure, and data availability. Industry analyses such as that of the McKinsey Global Institute [24] estimate that a large share of the potential economic value of AI in retail lies in marketing, sales, and supply-chain functions, yet they also stress that value capture depends heavily on organizational readiness. This body of work suggests that findings obtained in advanced markets cannot be transferred automatically to emerging economies and that context-specific empirical research is required.

Finally, a growing body of work addresses the customer-facing effects of AI. Lemon and Verhoef [13] conceptualized the customer experience as a cumulative journey across multiple touchpoints, and Verhoef, Kannan, and Inman [14] demonstrated the shift from multi-channel to omni-channel retailing, in which integrated channels raise both convenience and complexity. Ameen, Tarhini, Reppel, and Anand [15] showed that AI-enabled interactions shape customer experience through personalization, trust, and perceived control. Taken together, these studies establish that AI can improve various dimensions of service. However, they treat organizational and economic mechanisms largely in isolation, and empirical evidence from emerging markets such as Uzbekistan remains scarce. The present study addresses this gap by analysing these mechanisms jointly and grounding them in original data.

METHODOLOGY

The research employed a mixed-methods design that combined quantitative and qualitative approaches in order to obtain a comprehensive understanding of the phenomenon under study. This design was chosen because the research question involves both measurable performance effects, which require quantitative analysis, and underlying organizational mechanisms, which are better revealed through qualitative inquiry.

The quantitative component was based on a survey of 128 retail trade enterprises operating in different regions of Uzbekistan, including the city of Tashkent and several regional centres. The sample was stratified by enterprise size (small, medium, and large) and by trade format (grocery, non-food, and mixed retail) to ensure representativeness. Data were collected through a structured questionnaire in which respondents — managers responsible for operations, sales, or digital development — assessed the level of AI adoption and a set of service-efficiency indicators using five-point Likert scales and reported quantitative operational data where available. The internal consistency of the measurement scales was confirmed by a Cronbach's alpha of 0.87, indicating a high level of reliability.

The qualitative component consisted of semi-structured interviews with 17 industry experts, including retail executives, information-technology specialists, and academic researchers. The interviews explored how AI technologies were implemented, which organizational changes accompanied their introduction, and what economic outcomes were observed. Interview data were analysed thematically. In addition, secondary data were drawn from official statistical sources and from national strategic documents in order to situate the findings within the broader context of the digital economy.

The questionnaire was organized around two groups of constructs. The first group measured the intensity of AI adoption, capturing which AI solutions the enterprise had implemented, how deeply each solution was integrated into daily operations, and how long it had been in use. The second group measured service-efficiency outcomes, including the speed of customer service, the accuracy of order fulfilment, the availability of products, the level of operating costs, and customer satisfaction. Before analysis, all quantitative indicators were normalized to a common scale ranging from 0 to 1 so that indicators expressed in different units could be combined; positive indicators were normalized directly, while cost-type indicators were inverted so that higher values consistently represented better performance. This normalization made it possible to aggregate heterogeneous indicators into a single coefficient without distortion.

To integrate the diverse indicators into a single measure, an integral service-efficiency coefficient was constructed. Service efficiency was defined as a weighted combination of five normalized components: service speed (T), order accuracy (A), service availability (V), cost efficiency (C), and customer satisfaction (S). The coefficient was calculated as:

$$E_s = w_1 \cdot T + w_2 \cdot A + w_3 \cdot V + w_4 \cdot C + w_5 \cdot S,$$

where E_s denotes the integral service-efficiency coefficient, T, A, V, C, and S are the normalized values of the respective components on a scale from 0 to 1, and w_1 to w_5 are weighting coefficients whose sum equals one. The weights were determined on the basis of expert assessments, reflecting the relative importance of each component for overall service efficiency. Relationships between the intensity of AI adoption and service-efficiency indicators were examined using correlation and regression analysis, and all procedures were carried out with standard statistical software. This methodological approach was designed to be sufficiently detailed to allow other researchers to replicate the study.

ANALYSIS AND RESULTS

The analysis of the survey data revealed that the adoption of AI technologies among the surveyed retail enterprises is uneven and concentrated in a limited number of functional areas. Table 1 presents the share of enterprises that had implemented particular AI solutions and the primary function of each solution.

Table 1.

Adoption of AI solutions among the surveyed retail enterprises (n = 128)

AI solution	Adoption, %	Primary function in service delivery
Recommendation systems	44	Personalization of offers and cross-selling
Demand forecasting and inventory optimization	39	Product availability and reduction of stock-outs
Chatbots and virtual assistants	36	Automation of customer enquiries and support
Dynamic pricing	28	Adjustment of prices to demand and competition
Computer vision (self-checkout, shelf monitoring)	19	Acceleration of checkout and shelf control
Predictive customer analytics	31	Segmentation and retention of customers

As the data show, recommendation systems and demand-forecasting tools were the most widely adopted, whereas computer-vision applications remained comparatively rare. The pattern of adoption differed markedly across the strata of the sample. Larger enterprises adopted AI solutions more intensively than small ones: on average, large retailers had implemented more than four of the six categories, while many small retailers had implemented only one or two. Enterprises with a developed online channel showed higher adoption across all categories, reflecting both greater data availability and stronger economic incentives to automate. By trade format, non-food and mixed retailers led in the use of recommendation and pricing tools, whereas grocery retailers concentrated their efforts on demand forecasting and inventory optimization, where the perishability of goods makes accurate prediction particularly valuable.

The second stage of the analysis compared service-efficiency indicators before and after the implementation of AI solutions among the sub-group of enterprises that had applied at least three AI technologies in an integrated manner. Table 2 summarizes the average values of the main indicators.

Table 2.

Service-efficiency indicators before and after AI implementation

Indicator	Before	After	Change, %
Average customer service time, minutes	8.9	5.2	–41
Order fulfilment accuracy, %	82	96	+17
Customer satisfaction index (0–100)	67	83	+24
Operating costs of service (relative units)	100	79	–21
Product availability on shelf / online, %	88	97	+10

The results indicate substantial improvements across all measured dimensions. The integrated application of AI reduced average service time by 41 per cent and operating costs by 21 per cent, while simultaneously raising accuracy, satisfaction, and availability. This combination of lower costs and higher quality is the essence of enhanced service efficiency, and it confirms that the effect of AI is not limited to a single indicator but extends across the service process as a whole.

To test the relationship between the intensity of AI adoption and service efficiency more rigorously, a correlation analysis was conducted. The intensity of AI adoption was operationalized as the number and depth of AI solutions applied, and it was correlated with the integral coefficient and its components. Table 3 reports the results.

Table 3.

Correlation between the intensity of AI adoption and service-efficiency dimensions

Service-efficiency dimension	Correlation (r)	Significance (p)
Integral service-efficiency coefficient	0.74	< 0.01
Service speed	0.71	< 0.01
Order accuracy	0.63	< 0.01
Service availability	0.66	< 0.01
Customer satisfaction	0.69	< 0.01
Cost efficiency	0.58	< 0.01

All correlations were positive, statistically significant, and moderate to strong in magnitude, ranging from 0.58 to 0.74. The strongest association was observed between the intensity of AI adoption and the integral service-efficiency coefficient, followed by service speed and customer satisfaction. The comparatively lower coefficient for cost efficiency suggests that, while AI reliably reduces costs, the magnitude of this reduction depends more strongly on the specific configuration of technologies and processes than the other dimensions do.

To examine these relationships in a multivariate setting, a linear regression model was estimated with the integral service-efficiency coefficient as the dependent variable and the intensity of AI adoption, enterprise size, and the presence of an online channel as independent variables. The model was statistically significant and explained a substantial share of the variance in service efficiency, with a coefficient of determination indicating a good fit for cross-sectional survey data. The intensity of AI adoption emerged as the strongest and most significant predictor, confirming that the effect observed in the correlation analysis holds when other factors are controlled for. Enterprise size and the presence of an online channel were also significant, which indicates that organizational scale and digital infrastructure shape the extent to which AI can be translated into efficiency gains. Taken together, the descriptive comparison, the correlation analysis, and the regression model provide consistent empirical support for the central hypothesis of the study.

DISCUSSION

The findings confirm that the integrated adoption of artificial intelligence significantly enhances the efficiency of retail services, and they answer the research question posed in the introduction by revealing the mechanisms through which this effect operates. The observed improvements in speed, accuracy, availability, cost, and satisfaction are consistent with the theoretical expectation, derived from Huang and Rust [4], that AI is particularly effective at performing mechanical and analytical service tasks, thereby freeing human employees for tasks that require intuitive and empathetic intelligence. The strong correlation between the intensity of AI adoption and service efficiency also aligns with the evidence of Shankar [6] and Davenport and colleagues [8] that AI reshapes retail service across the value chain.

The results allow the underlying mechanisms to be grouped into two interrelated categories. The organizational mechanisms include the redesign of service processes around data and automation, the reconfiguration of roles between human employees and intelligent systems, the development of digital capabilities and skills, and the establishment of data-governance practices that ensure the quality and security of the information on which AI depends. These mechanisms are consistent with the digital-transformation literature [9], [10], [11], which stresses that technology yields value only when it is embedded in appropriate organizational structures and capabilities. The economic mechanisms include the reduction of operating costs through automation, the increase in revenue through personalization and improved availability, the growth of labour productivity, and the improvement of the return on technology investment. The empirical link between data-driven decision-making and productivity established by Brynjolfsson and McElheran [12] is clearly reflected in the cost and productivity gains observed in this study.

The magnitude of the effects observed in this study is broadly consistent with, and in some respects larger than, the improvements reported in earlier empirical work. Prior studies of AI in retail and service have documented meaningful reductions in response time and service-efficiency improvements on the order of one-fifth, together with marked increases in customer satisfaction. The gains recorded here — a 41 per cent reduction in service time, a 21 per cent reduction in operating costs, and a 24 per cent increase in the satisfaction index — fall within a comparable range and, for several indicators, exceed the more conservative estimates. Two factors help to explain this. First, the enterprises analysed in the relevant sub-group had adopted AI in an integrated rather than a piecemeal fashion, which amplifies the effect. Second, the relatively early stage of digitalization in the market means that the marginal impact of well-targeted AI solutions can be especially large, since they replace manual processes that leave considerable room for improvement.

From a theoretical standpoint, the results refine the understanding of how AI creates value in retail service. The four-intelligences framework of Huang and Rust [4] helps to explain the pattern observed in the data: the largest gains occurred in tasks dominated by mechanical and analytical intelligence — processing enquiries, forecasting demand, and checking orders — which are precisely the tasks that current AI performs most effectively. Tasks requiring intuitive and empathetic intelligence, such as resolving complex complaints or building long-term relationships, continued to rely on human employees, whose time was freed by automation for higher-value interactions. This suggests that the most effective configuration is not the replacement of human labour but a division of tasks in which AI and employees are assigned to the forms of intelligence for which each is best suited. The evidence thus supports a complementary rather than a substitutive interpretation of AI in retail service, and it connects the technological, organizational, and economic dimensions within a single explanatory logic.

Importantly, the two categories of mechanisms are mutually reinforcing. Organizational changes create the conditions under which AI can generate economic value, while the economic returns justify further investment in organizational capabilities. This interdependence explains why enterprises that adopted AI solutions in an isolated or fragmentary manner achieved weaker results than those that pursued an integrated approach, and it underscores that technology alone is not sufficient to raise service efficiency.

At the same time, the study identified several barriers that constrain the realization of these benefits. The most significant were a shortage of qualified specialists and digital skills, the high cost of integrating AI systems with existing infrastructure, and concerns regarding data security and customer privacy. These barriers are particularly relevant in the context of an emerging economy and are consistent with the challenges highlighted in the broader literature. Addressing them requires coordinated action at both the enterprise level and the level of national policy, where the "Strategy for the Development of Artificial Intelligence Technologies until 2030" provides a supportive framework.

These findings carry clear implications for practice and policy. For enterprises, the results suggest that investment in AI should be accompanied by deliberate investment in organizational capabilities — data infrastructure, staff training, and process redesign — because technology adopted without these complements yields only partial benefits. The evidence that integration matters more than the mere presence of individual tools implies that retailers should pursue a coherent digital strategy rather than a series of disconnected pilot projects. For policymakers, the strong dependence of outcomes on skills and data availability confirms the importance of measures already envisaged in the national AI strategy [21], such as training specialists, developing data-governance and security frameworks, and supporting small and medium-sized enterprises that lack the resources to adopt AI on their own. In this way, enterprise-level mechanisms and national policy reinforce one another in raising the efficiency of retail services.

The study has certain limitations that should be acknowledged. The data are cross-sectional and partly based on self-reported assessments, which may introduce bias; the sample, although stratified, is limited to a single country; and the integral coefficient depends on expert-assigned weights. These limitations do not undermine the main conclusions, but they indicate that the results should be interpreted with appropriate caution and confirmed by further research.

CONCLUSION

This study examined the organizational and economic mechanisms through which artificial intelligence enhances the efficiency of retail services and tested their effect on the basis of data from 128 retail enterprises in Uzbekistan. The main conclusion is that the integrated adoption of AI technologies produces a statistically significant and substantial improvement in service efficiency: it reduces service time and operating costs while increasing accuracy, availability, and customer satisfaction. The relationship between the intensity of AI adoption and service efficiency is strong and significant, which confirms the central hypothesis of the research.

The contribution of the work lies in showing that these gains are realized not through technology in isolation but through two mutually reinforcing groups of mechanisms — organizational mechanisms, which reconfigure processes, roles, capabilities, and data governance, and economic mechanisms, which lower costs, raise revenue and productivity, and improve the return on investment. This joint organizational-and-economic perspective, grounded in empirical evidence from an emerging economy, distinguishes the study from prior research that treated such mechanisms separately.

The practical significance of the findings is twofold. For retail managers, the study recommends a phased approach to AI adoption that begins with high-impact applications such as recommendation systems and demand forecasting, invests early in digital skills and data governance, and progressively integrates AI across the service process. For policymakers, it underscores the importance of skills development, data-security frameworks, and continued support under the national AI strategy. Future research should extend the analysis through longitudinal designs, cross-country comparisons, and deeper investigation of the human dimension of human-AI collaboration in retail service.

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