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Article

Improving the Management of Innovative Marketing Processes at Enterprises on the Basis of Digital Platforms and Artificial Intelligence Technologies

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Abstract: The article develops a conceptual and applied framework for improving the management of innovative marketing processes at enterprises on the basis of digital platforms and artificial intelligence (AI) technologies. A six-layer architecture of an AI-driven innovative marketing management system is proposed, in which data sources, the digital platform, AI services, marketing processes, governance and competences are treated as interdependent elements. A digital marketing maturity index (DMI) with a five-level scale is constructed and applied to a sample of 144 industrial and trade enterprises of the Republic of Uzbekistan surveyed in 2025–2026. The predictive capability of the framework is tested on the monthly sales data of eleven pilot enterprises (2019–2025, 726 series-months): an ensemble of gradient boosting and long short-term memory networks reduces the mean absolute percentage error of demand forecasts from 24.7 % (expert judgement) to 8.4 %. Panel regression on 144 enterprises over five years (720 observations) with fixed effects shows that a one-point increase in the DMI is associated with an increase in the return on marketing investment of 21.4 percentage points and a reduction in the commercialization cycle of 1.9 months. A six-stage roadmap of implementation with a duration of 20 months and an estimated cost of 2.8–4.1 % of annual revenue is elaborated, and three scenarios of development up to 2030 are quantified. The results can be used by industrial enterprises, sectoral ministries and bodies of state support of entrepreneurship.

Keywords: innovative marketing, digital platform, artificial intelligence, machine learning, demand forecasting, customer data platform, digital maturity, panel regression, ROMI, Uzbekistan.

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1. Introduction

Over the past decade the technological base of marketing management has changed more profoundly than at any time since the emergence of mass media advertising. Two shifts are of decisive importance. The first is the phantomization of markets: a substantial and growing part of the interaction between producer and consumer takes place inside digital environments marketplaces, social networks, mobile applications, messengers which simultaneously mediate the transaction and record it. The second is the maturing of artificial intelligence technologies, which have moved from experimental pilots into ordinary business operation, becoming affordable for medium-sized and even small enterprises through cloud services and application programming interfaces.

For the innovative marketing concept these shifts are not merely instrumental improvements. Innovative marketing presupposes the ability of an enterprise to identify latent needs, to test hypotheses quickly and to bring novelties to the market before competitors. Each of these abilities is limited, in the traditional configuration, by the cost and the speed of obtaining market information. A digital platform reduces the cost of collecting data by orders of magnitude, and artificial intelligence reduces the cost and time of converting the data into a decision. In other words, the technologies discussed here relax exactly those constraints that historically restricted the practical realisation of the innovative marketing concept.

At the same time, empirical observation of enterprises in the Republic of Uzbekistan reveals a paradoxical picture. Digital instruments are being adopted rapidly — the share of enterprises using customer relationship management or analytical systems increased from 6.2 % in 2018 to 36.1 % in 2025 yet the effect of this adoption on marketing performance remains modest and highly uneven. A significant number of enterprises acquire software licences without redesigning the underlying processes, so the new system reproduces the old decision-making logic in a more expensive form. This phenomenon, well known in the literature as the "productivity paradox" of information technologies, indicates that the object of management improvement is not the technology as such but the process in which it is embedded.

The aim of the study is to develop and empirically substantiate an approach to improving the management of innovative marketing processes at enterprises on the basis of digital platforms and artificial intelligence technologies. The following tasks are solved: (i) to systematise the theoretical foundations and to identify the gaps in the existing literature; (ii) to design a layered architecture of an AI-driven innovative marketing management system; (iii) to construct and validate a digital marketing maturity index; (iv) to assess empirically the state of digital maturity of enterprises of Uzbekistan and the barriers to further progress; (v) to test the practical capability of machine learning models in the tasks of demand forecasting and customer segmentation; (vi) to estimate econometrically the influence of digital maturity on marketing performance; (vii) to elaborate a roadmap of implementation and to quantify the scenarios of development up to 2030.

The scientific novelty of the study consists in the integration of three elements that are usually examined separately: the architectural model of the digital marketing system, the quantitative index of its maturity and the econometric estimation of the effect of this maturity on enterprise performance. This integration allows the transition from the qualitative statement that "digitalisation is useful" to the quantified answer to the question of how much a movement of one maturity level is worth for a particular enterprise.

The theoretical understanding of platforms originates in the theory of two-sided markets developed by J.-C. Rochet and J. Tirole, who demonstrated that the pricing logic of an intermediary connecting two groups of agents differs fundamentally from that of a conventional firm [1]. A. Hagiu and J. Wright specified the boundary between platforms and resellers, showing that the choice between the two modes depends on where the relevant information about the customer resides [2]. G. Parker, M. Van Alstyne and S. Choudary generalised these findings into a managerial framework of platform revolution, emphasising network effects and the shift of value creation from internal production to external ecosystems [3]. From the standpoint of the present study, the essential implication is that an enterprise operating through platforms is simultaneously a supplier and a data-generating agent, and its marketing competitiveness increasingly depends on the ability to appropriate and to interpret the data trace of its own transactions.

The systematic incorporation of AI into marketing theory begins with the work of T. Davenport and colleagues, who proposed a classification of AI applications by the type of intelligence involved mechanical, thinking and feeling and argued that the boundary of automation moves progressively upward along this scale [4]. M. Huang and R. Rust developed a strategic framework in which each type of intelligence corresponds to a distinct marketing task: mechanical intelligence to standardisation, thinking intelligence to personalisation and feeling intelligence to relationalisation [5]. Empirical studies confirm significant effects of AI-based personalisation on conversion and customer lifetime value [6], [7], while research on algorithmic pricing documents both efficiency gains and risks of tacit collusion [8].

The idea that the effect of a technology depends on the organisational capacity to absorb it goes back to the concept of absorptive capacity of W. Cohen and D. Levinthal [9] and was subsequently formalised in maturity models. The Capability Maturity Model and its numerous derivatives established the five-level scale that is widely used today [10]. In the marketing domain, digital maturity frameworks have been proposed by consulting practice and by academic authors [11; 12], but they differ considerably in composition and are rarely validated against financial outcomes. The methodological gap identified in the literature is therefore twofold: the indices are seldom weighted on an explicit basis, and their predictive validity is rarely tested [13].

Demand forecasting has traditionally relied on statistical time-series methods — exponential smoothing and autoregressive integrated moving average models [14]. The results of the M4 and M5 forecasting competitions demonstrated that machine learning methods, and particularly gradient boosting and combinations of statistical and neural approaches, systematically outperform pure statistical benchmarks on retail data with rich exogenous information [15], [16]. In marketing analytics, unsupervised methods of segmentation, notably k-means clustering applied to recency–frequency–monetary features, remain the workhorse of practical customer analytics [17]. The literature nevertheless emphasizes that the accuracy of a model is a necessary but not a sufficient condition of value: the decisive factor is whether the forecast is integrated into planning routines [18].

In the domestic literature the questions of digital transformation of the economy, of the development of electronic commerce and of the marketing support of innovation activity have received significant attention [19]. These works establish the macroeconomic context and describe the institutional instruments of digitalization. However, three gaps remain [20]. First, the level of analysis is predominantly macroeconomic, whereas the mechanism by which digital technologies affect the marketing process operates at the level of the individual enterprise. Second, digital maturity is generally described qualitatively, without a measurable index that could be compared across enterprises [21]. Third, the empirical assessment of the effect of artificial intelligence tools on marketing performance in the conditions of Uzbekistan has not, to the knowledge of the author, been carried out on panel data. The present study is designed to fill these gaps.

Table 1. Evolution of the technological base of marketing management and the corresponding managerial paradigm

Generation / period	Dominant technology	Unit of analysis	Decision cycle	Role of the marketer
Analogue marketing, up to 1990s	Mass media, paper reporting	Market segment	Quarter — year	Interpreter of aggregate data

Generation / period	Dominant technology	Unit of analysis	Decision cycle	Role of the marketer
Database marketing, 1990–2005	Relational databases, direct mail	Customer group	Month — quarter	Designer of campaigns
Digital marketing, 2005–2015	Web analytics, CRM, search and social advertising	Session and channel	Week — month	Operator of channels
Data-driven marketing, 2015–2022	Big data, cloud platforms, A/B testing infrastructure	Individual customer	Day — week	Analyst and experimenter
AI-driven marketing, since 2022	Machine learning, generative models, autonomous agents	Micro-moment of interaction	Minutes — hours	Architect of algorithms and processes

Source: compiled by the author on the basis of.

Table 1 makes explicit the central managerial consequence of the technological evolution: as the decision cycle contracts from quarters to hours, the human marketer physically ceases to be able to take every decision individually. The function of the marketing manager is displaced from decision-making to the design of the rules and the algorithms by which decisions are taken automatically, and to the control of their outcomes. This displacement is precisely what the improvement of management proposed in this article is intended to organize.

2. Materials and Methods

The study employs a mixed design combining a cross-sectional survey, a panel econometric estimation, a computational experiment with machine learning models and a scenario projection. Four sources of empirical data are used.

The second source is the financial and management reporting of the surveyed enterprises for 2021–2025, which forms the panel of 720 enterprise-year observations. The first source is a questionnaire survey of 144 enterprises of the Bukhara, Navoi, Samarkand and Kashkadarya regions, conducted from September 2025 to March 2026. The sample includes 28 large, 72 medium and 44 small enterprises of the manufacturing industry, food processing, light industry and wholesale trade. The questionnaire contained 46 items covering the technological, process, data, competence and governance dimensions of the marketing function. The respondents were heads of marketing, commercial or sales departments and, in 39 cases, chief executives.

The official statistics of the Statistics Agency under the President of the Republic of Uzbekistan and of the Ministry of Digital Technologies are used for the macroeconomic context and for the calibration of the scenarios. The third source is the monthly sales data of eleven pilot enterprises for the period January 2019 – December 2025, comprising 726 series-months across 34 product categories, together with exogenous variables (price, promotional activity, holidays, seasonal indices, exchange rate). These data are used for the computational experiment with forecasting models.

The digital marketing maturity index (DMI) is constructed as a weighted composite of five dimensions, each measured by four to six items on a five-point scale: technological infrastructure (D1), data and analytics (D2), process integration (D3), competences and organization (D4), governance and measurement (D5). The index is expressed on a scale from 1 to 5 and interpreted through five maturity levels, from L1 “initial” to L5 “intelligent”.

The weights of the dimensions were obtained by the analytic hierarchy process on the basis of pairwise comparisons by twenty-one experts (nine marketing practitioners, seven information technology managers and five academic researchers). The consistency ratio equals 0.047, which is below the conventional threshold of 0.1 and confirms the coherence of expert judgements. The internal consistency of the resulting scale is high (Cronbach's alpha = 0.912), and exploratory factor analysis confirms the five-factor structure, explaining 71.8 % of the total variance with all loadings above 0.55.

The computational experiment compares eight approaches to demand forecasting: expert judgement of the enterprise's own managers (recorded ex ante and preserved for comparison), a naive seasonal benchmark, ARIMA, exponential smoothing (ETS), random forest, gradient boosting (XGBoost), a long short-term memory neural network (LSTM) and an ensemble of the last two with weights optimized on the validation set. The data were split chronologically: January 2019 – December 2023 for training, 2024 for validation and 2025 for the test sample, which excludes look-ahead bias. Accuracy is measured by the mean absolute percentage error (MAPE), the root mean squared error (RMSE) and the mean absolute scaled error (MASE).

Customer segmentation was performed by k-means clustering on eight normalized features describing purchase behavior and responsiveness to novelties, using the data of the pilot enterprises' loyalty programs (about 47 thousand active customers). The number of clusters was determined by the silhouette coefficient and the elbow criterion; the four-cluster solution yields a silhouette of 0.61.

The influence of digital maturity on marketing performance is estimated on the balanced panel of 144 enterprises over 2021–2025 (720 observations) by the model:

$$Y_{it} = \alpha_i + \beta_1 DMI_{it} + \beta_2 AI_{it} + \beta_3 DATA_{it} + \beta_4 SIZE_{it} + \beta_5 AGE_{it} + \beta_6 EXP_{it} + \beta_7 COMP_{it} + \lambda_t + \varepsilon_{it},$$

where Y_{it} denotes alternately the return on marketing investment (ROMI), the duration of the commercialization cycle and the share of new products in revenue; DMI is the digital marketing maturity index; AI is a count of the artificial intelligence use cases in regular operation; DATA is the share of managerial decisions supported by formalized analytics; SIZE is the natural logarithm of the number of employees; AGE is the age of the enterprise; EXP is the share of exports in revenue; COMP is the share of staff with data-analytical competences; α_i are unobserved individual effects; λ_t are year effects; ε_{it} is the disturbance term.

The specification was estimated by fixed effects and random effects; the choice between them was made on the basis of the Hausman test. Standard errors are clustered at the enterprise level to accommodate heteroscedasticity and within-firm autocorrelation. Multicollinearity is controlled by variance inflation factors, all of which remain below 4.2. To mitigate the risk of reverse causality the explanatory variables enter with a one-year lag, and a robustness check is performed with the system generalized method of moments. Computations were carried out in Stata 17, EViews 12 and Python 3.11 (scikit-learn, XGBoost, TensorFlow).

The scenario projection to 2030 is constructed by applying the estimated elasticities to three trajectories of the digital maturity index: an inertial trajectory (annual growth of 0.08 points), a baseline trajectory (0.19 points) and an optimistic trajectory (0.31 points), calibrated respectively on the observed growth of the least active third of the sample, of the whole sample and of the leading decile.

3. Results and Discussion

The digital environment in which the enterprises of Uzbekistan operate has changed rapidly. Internet penetration rose from 52.3 % of the population in 2018 to 90.6 % in 2025; the turnover of electronic commerce increased from 0.9 to 21.3 trillion soums, that is, more than twenty-three-fold; the share of enterprises employing customer relationship management or analytical systems grew from 6.2 % to 36.1 % (Figure 1).

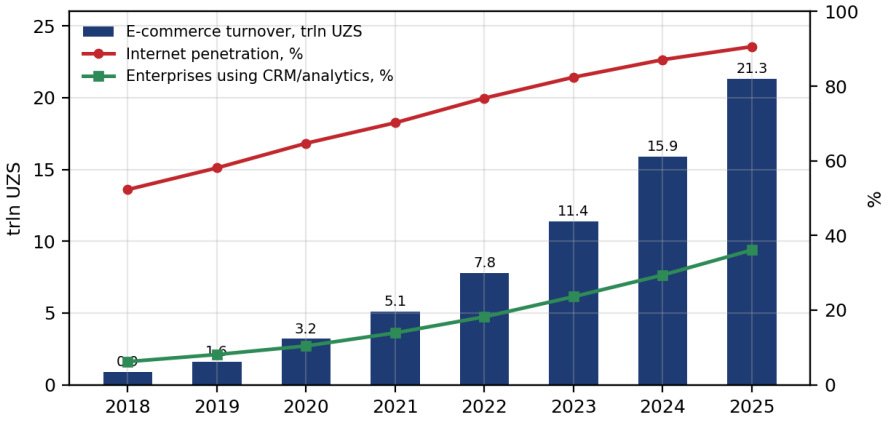


Figure 1. Development of the digital environment of the Republic of Uzbekistan, 2018–2025 (compiled by the author on the basis of the data of the Statistics Agency and the Ministry of Digital Technologies)

The growth of infrastructure indicators nevertheless outpaces the growth of the analytical use of the resulting data. In the surveyed sample only 27.8 % of enterprises report that more than half of their marketing decisions are based on formalised analytics, while 41.0 % continue to rely predominantly on managerial experience. The gap between connectivity and analytical capability constitutes the principal reserve of improvement identified in this study.

The proposed architecture is presented in Figure 2. It comprises six layers. The lower layer of data sources unifies internal systems (customer relationship and enterprise resource planning), external platforms (marketplaces, social networks) and behavioural telemetry. The platform layer performs the physical and semantic integration of these flows and maintains a single customer profile. The layer of artificial intelligence services converts the integrated data into predictions and recommendations. The process layer is the core of the architecture: it defines at which point of the innovative marketing cycle a particular prediction is consumed and by whom. The governance layer establishes the rules of data quality, privacy, algorithmic transparency and performance measurement. The competence layer provides the human capability without which the preceding layers remain inert [22].



Figure 2. Six-layer architecture of the AI-driven innovative marketing management system of the enterprise (developed by the author)

The methodological significance of the layered representation lies in the identification of the binding constraint. In the enterprises examined, the constraint is almost never located in the layer of artificial intelligence services, which are available on the market as commodity products. In 62.5 % of the cases the constraint is in the platform layer, where the data remain fragmented, and in 29.9 % of the cases in the competence layer. The practical implication is that investment in advanced models before the integration of data produces no measurable return a conclusion supported by the econometric results reported below [23].

Table 2. Comparative characteristics of the types of digital platforms used by the enterprises of the sample

Type of platform	Principal function in innovative marketing	Share of enterprises using, %	Average share in revenue, %	Data ownership	Cost model
Own e-commerce website / application	Direct sales, full behavioural telemetry, hypothesis testing	34.7	9.4	Full	Capital and support costs
National marketplaces	Rapid market access, assortment testing, price benchmarking	58.3	17.8	Partial (aggregated)	Commission 8–15 %
Global marketplaces	Export channel, access to foreign demand signals	12.5	4.1	Partial	Commission 10–20 %
Social commerce and messengers	Communication, micro-influence, community feedback	71.5	11.2	Limited	Advertising budget
B2B procurement platforms	Industrial sales, tender participation	27.1	13.6	Limited	Subscription and fees
Customer data platform (CDP)	Unification of profiles, segmentation, orchestration	18.1	—	Full	Subscription per profile
Cloud AI services (API)	Forecasting, generation of content, recommendations	22.9	—	Full (input data)	Pay-per-use

Source: author's survey of 144 enterprises, 2025–2026. The shares do not sum to 100 % because enterprises use several types of platforms simultaneously.

Table 2 reveals an important asymmetry. The most widely used channels social commerce and national marketplaces provide the least complete ownership of data, whereas the channels that guarantee full data ownership are used by only about one third of enterprises. Consequently, the majority of the enterprises observe their own market through an intermediary's aggregated reporting, which is sufficient for operational sales management but insufficient for the generation of innovative hypotheses [24].

The structure of the digital marketing maturity index and the expert weights are presented in Table 3. The dimension of data and analytics received the highest weight (0.257), followed by process integration (0.231); the technological infrastructure, contrary to the intuition frequently encountered in practice, occupies only the third position (0.204).

Table 3. Structure, indicators and weights of the digital marketing maturity index (DMI)

Dimension	Content of the indicators	Number of items	Weight	Sample mean (1–5)
D1. Technological infrastructure	CRM/ERP systems, e-commerce channel, marketing automation, integration interfaces	5	0.204	2.61
D2. Data and analytics	Unified customer profile, data quality, depth of analytics, use of predictive models	6	0.257	2.14
D3. Process integration	Embedding of analytics in the marketing cycle, experimentation routine, speed of feedback	5	0.231	2.05
D4. Competences and organisation	Data-analytical staff, product management, cross-functional teams, training	4	0.176	2.38
D5. Governance and measurement	KPI system, data privacy and security, algorithmic transparency, budget control	4	0.132	2.47
Aggregate DMI	—	24	1.000	2.31

Source: author's calculations; analytic hierarchy process, 21 experts, consistency ratio CR = 0.047; Cronbach's alpha = 0.912.

The distribution of enterprises by maturity level is strongly asymmetric and clearly differentiated by size (Figure 3). Among large enterprises 39.3 % have reached the fourth or fifth level, whereas among small enterprises this share is only 6.8 %, and no small enterprise in the sample has attained the fifth level. Conversely, 38.6 % of small enterprises remain at the initial level, where digital instruments are used sporadically and without integration [25].

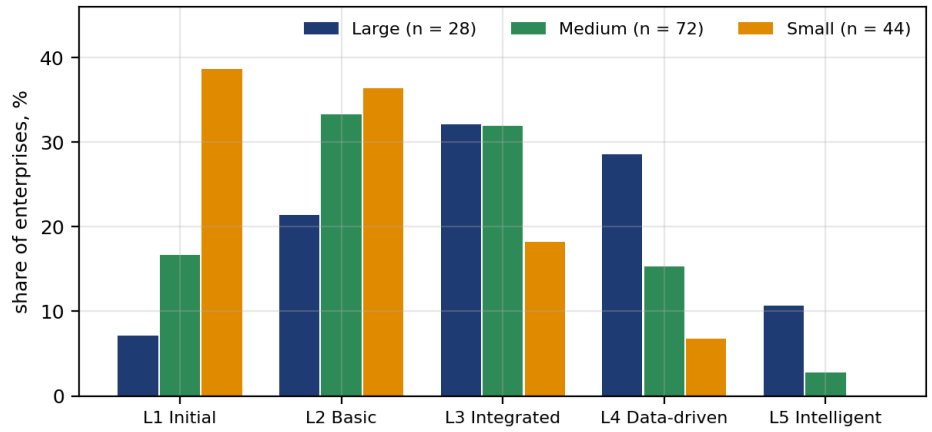


Figure 3. Distribution of the surveyed enterprises by the level of digital marketing maturity and size group, % (n = 144, author's survey)

The economic differentiation across maturity levels is presented in Table 4. The movement from the first to the fifth level is associated with an increase in the return on marketing investment from 61 % to 247 %, with a reduction of the commercialisation cycle from 16.8 to 6.9 months and with a growth of the share of new products in revenue from 4.2 % to 27.9 %. The relationship is monotonic across all indicators.

Table 4. Performance indicators of the enterprises by the level of digital marketing maturity (n = 144)

Maturity level	Number of enterprises	Share, %	Average DMI	ROMI, %	Commercialisation cycle, months	Share of new products, %	Return on sales, %
L1 — initial	31	21.5	1.34	61	16.8	4.2	6.4
L2 — basic	45	31.3	2.06	97	14.1	8.7	9.1
L3 — integrated	40	27.8	2.79	148	11.3	14.6	12.8
L4 — data-driven	23	16.0	3.61	196	8.7	21.4	16.2
L5 — intelligent	5	3.4	4.42	247	6.9	27.9	19.7
Total / average	144	100.0	2.31	121	12.6	12.1	10.9

Source: author's calculations on the basis of the survey and the financial reporting of the enterprises for 2025.

The frequency of the application of particular artificial intelligence use cases and the expert assessment of their effect on marketing performance are shown in Figure 4. A pronounced inverse relationship is observed between the frequency of adoption and the assessed effect: the most widely adopted applications generative content production and chatbots are also those with the lowest assessed effect, whereas the applications with the highest effect demand forecasting, dynamic pricing and recommender systems are adopted by fewer than one enterprise in four [26].

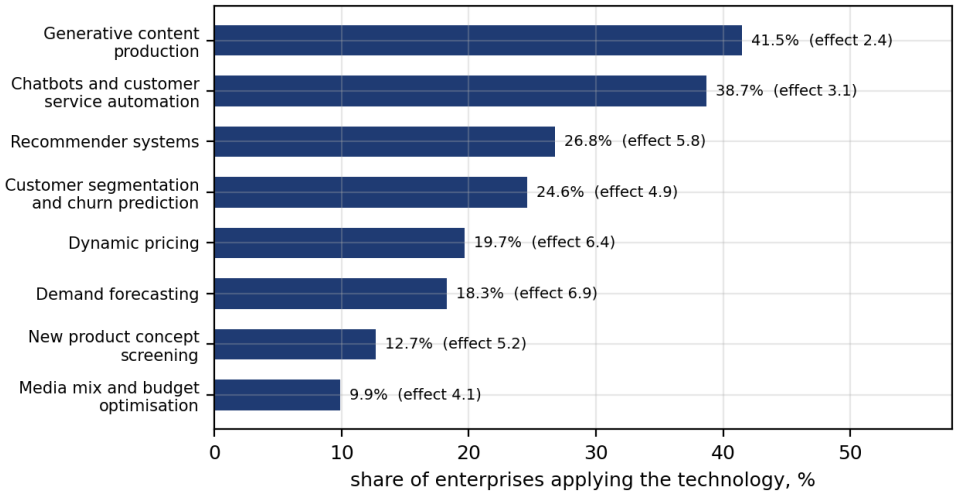


Figure 4. Adoption of artificial intelligence use cases in marketing and the expert assessment of their effect (10-point scale) in the surveyed enterprises, % (n = 142 enterprises using at least one digital instrument)

The explanation of this inversion is instructive. Content generation and conversational agents can be implemented on top of an unintegrated data landscape, since they require little proprietary data; forecasting, pricing and recommendation require a unified and clean data base and a redesigned decision process. Enterprises therefore adopt first what is easy rather than what is valuable. This is the empirical manifestation of the platform-layer constraint identified in section 4.2.

Table 5. Artificial intelligence use cases in the innovative marketing cycle and the measured effects at the pilot enterprises

Stage of the marketing cycle	AI use case	Measured effect	Value before	Value after	Change, %
Idea generation	Mining of reviews, queries and social listening for unmet needs	Number of validated ideas per year	14	37	+164.3
Screening of concepts	Predictive scoring of concepts by expected demand	Share of successful launches, %	31.0	54.0	+74.2
Design of the offer	Conjoint analysis automation, generative packaging variants	Duration of the design phase, weeks	9.4	5.1	–45.7
Pricing	Dynamic pricing with elasticity estimation	Gross margin, %	22.6	26.9	+19.0
Channel and media planning	Media mix optimisation, budget allocation model	Cost per acquisition, thousand UZS	78.4	56.1	–28.4
Launch and campaigns	Generative content, automated A/B testing	Number of tested creatives per month	6	41	+583.3
Customer management	Churn prediction and next-best-offer recommendation	Annual churn rate, %	24.8	17.3	–30.2
Post-launch monitoring	Demand forecasting and inventory alignment	Forecast error (MAPE), %	24.7	8.4	–66.0

Source: author's calculations on the basis of the data of eleven pilot enterprises; comparison of the twelve months preceding and following implementation.

The comparison of forecasting approaches on the test sample of 2025 is presented in Figure 5 and Table 6. The ensemble of gradient boosting and the long short-term memory network attains a mean absolute percentage error of 8.4 %, which is 2.9 times lower than the error of expert judgement and 1.8 times lower than that of the best classical statistical model.

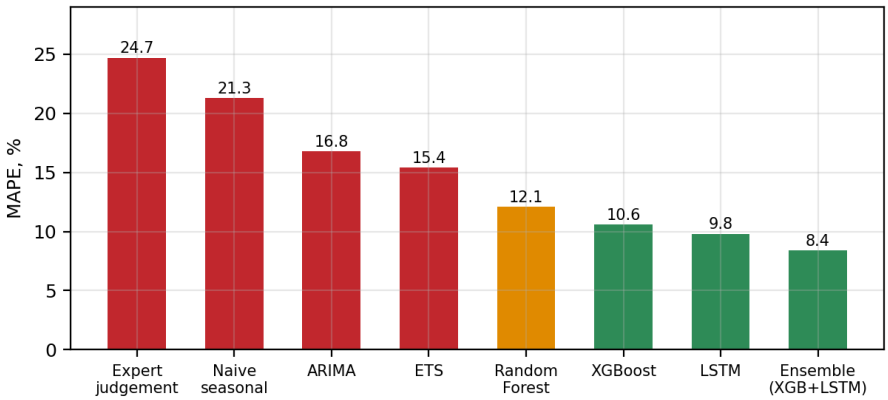


Figure 5. Accuracy of demand forecasting methods on the test sample (mean absolute percentage error, %), 34 product categories of eleven pilot enterprises, 2025

Table 6. Comparative accuracy of demand forecasting methods (test sample: January–December 2025, 726 series-months)

Method	MAPE, %	RMSE, units	MASE	Rank	Estimated implementation cost, mln UZS	Payback period, months
Expert judgement of managers	24.7	1 842	1.00	8	0	—
Naive seasonal benchmark	21.3	1 596	0.87	7	2	1.4
ARIMA $(p,d,q)(P,D,Q)_s$	16.8	1 271	0.69	6	18	4.7
ETS (exponential smoothing)	15.4	1 184	0.64	5	16	3.9
Random forest	12.1	947	0.51	4	42	6.1
XGBoost (gradient boosting)	10.6	836	0.45	3	48	5.4
LSTM neural network	9.8	781	0.42	2	74	7.8
Ensemble XGBoost + LSTM	8.4	674	0.36	1	89	6.9

Source: author's computations in Python 3.11 (scikit-learn, XGBoost, TensorFlow). MASE is normalised to the expert benchmark.

Two conclusions follow from Table 6. First, the marginal gain in accuracy declines as the complexity of the model increases, whereas the cost of implementation grows more than proportionally: the transition from ETS to gradient boosting reduces the error by 4.8 percentage points at a cost of 32 million soums, while the further transition to the ensemble reduces it by only 2.2 percentage points at an additional cost of 41 million. For a medium-sized enterprise the economically rational choice is therefore gradient boosting rather than the most accurate configuration. Second, even the simplest formalised method outperforms expert judgement, which indicates that the principal reserve lies not in the sophistication of the algorithm but in the very transition from intuitive to model-based forecasting.

The results of customer segmentation are presented in Figure 6. Four segments were identified with a silhouette coefficient of 0.61. The segment of "innovation adopters", representing 19.4 % of the customer base, generates 34.7 % of the revenue from new products, which makes it the priority target of the testing of novelties.

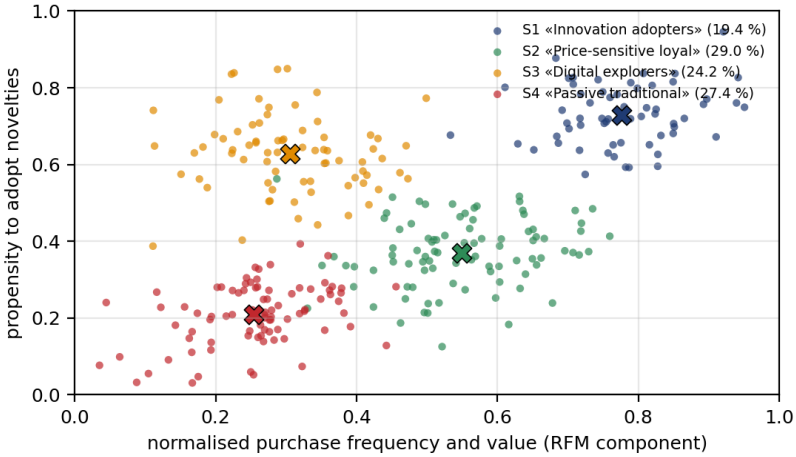


Figure 6. Results of the k-means segmentation of the customer base of the pilot enterprises (four clusters, about 47 thousand active customers, silhouette coefficient 0.61)

Table 7. Characteristics of the identified customer segments and the recommended marketing actions

Segment	Share of customers, %	Share of revenue, %	Share of revenue from new products, %	Average check, thousand UZS	Priority marketing action
S1. Innovation adopters	19.4	31.2	34.7	412	Early access, beta testing, referral programmes
S2. Price-sensitive loyal	29.0	34.6	21.8	268	Volume incentives, subscription formats
S3. Digital explorers	24.2	18.9	28.4	194	Content-driven engagement, personalised recommendations
S4. Passive traditional	27.4	15.3	15.1	157	Reactivation campaigns, simplified offer

Source: author's calculations on the basis of the loyalty programme data of the pilot enterprises.

The descriptive statistics of the panel variables are reported in Table 8, and the estimation results in Table 9. The Hausman test rejects the random effects specification ($\chi^2 = 34.16$; $p = 0.000$), so the interpretation is based on the fixed effects estimates.

Table 8. Descriptive statistics of the panel variables (N = 144 enterprises, T = 5 years, 720 observations)

Variable	Notation	Mean	Std. deviation	Minimum	Maximum
Return on marketing investment, %	ROMI	121.4	58.7	12.0	294.0
Commercialisation cycle, months	CYCLE	12.6	4.3	5.0	26.0
Share of new products in revenue, %	NPS	12.1	8.4	0.0	34.0
Digital marketing maturity index	DMI	2.31	0.87	1.00	4.68
Number of AI use cases in operation	AI	1.74	1.92	0	8
Share of analytics-based decisions, %	DATA	38.6	21.4	0.0	92.0
Enterprise size (ln employees)	SIZE	5.36	1.14	2.89	8.42
Enterprise age, years	AGE	17.9	9.8	2.0	48.0
Export share, %	EXP	15.7	15.1	0.0	68.0
Share of staff with data competences, %	COMP	8.4	6.9	0.0	31.0

Source: author's calculations on the basis of the survey and financial reporting for 2021–2025.

Table 9. Results of the panel estimation of the influence of digital maturity on marketing performance

Variable	Model 1: ROMI (FE)	Model 2: ROMI (RE)	Model 3: CYCLE (FE)	Model 4: NPS (FE)
DMI (t–1)	21.43*** (3.86)	19.87*** (3.42)	–1.92*** (0.34)	4.71*** (0.82)
AI (t–1)	6.82*** (1.94)	6.41*** (1.81)	–0.47*** (0.16)	1.36*** (0.39)
DATA (t–1)	0.514*** (0.147)	0.489*** (0.138)	–0.038** (0.017)	0.104*** (0.031)
SIZE	4.16* (2.28)	5.03** (2.04)	–0.21 (0.24)	0.62 (0.51)
AGE	–0.34** (0.16)	–0.29* (0.15)	0.06** (0.03)	–0.09** (0.04)
EXP	0.278*** (0.094)	0.264*** (0.088)	–0.019* (0.011)	0.061*** (0.021)
COMP	1.147*** (0.362)	1.086*** (0.334)	–0.093** (0.041)	0.218*** (0.074)
Constant	12.68 (9.84)	18.42** (8.61)	21.36*** (1.92)	–6.14** (2.87)
Year effects	included	included	included	included
R^2 (within)	0.614	0.598	0.567	0.641
F / Wald statistic	F = 71.2***	χ^2 = 384.7***	F = 58.4***	F = 79.6***
Observations	720	720	720	720

*Note: enterprise-clustered standard errors in parentheses; *** p < 0.01; ** p < 0.05; * p < 0.10. Hausman test: χ^2 = 34.16; p = 0.000. Source: author's calculations (Stata 17).*

The estimates admit a direct managerial interpretation. An increase of the digital marketing maturity index by one point — that is, the movement of approximately one maturity level raises the return on marketing investment by 21.4 percentage points, shortens the commercialisation cycle by 1.9 months and increases the share of new products in revenue by 4.7 percentage points. Each additional artificial intelligence use case brought into regular operation adds 6.8 percentage points of ROMI, which corresponds to the incremental logic of the layered architecture.

The coefficient on the share of staff with data-analytical competences deserves separate attention: an increase of this share by ten percentage points is associated with a rise of ROMI of 11.5 percentage points, an effect comparable in magnitude to that of half a maturity level. This confirms that human capital is not a peripheral condition of digitalisation but one of its principal drivers. The negative and significant coefficient on the age of the enterprise reproduces the effect of organisational inertia established in the previous studies of the author on the same population.

Robustness checks confirm the stability of the results. The re-estimation by the system generalised method of moments with lagged instruments preserves the sign and the significance of the DMI coefficient ($\beta = 19.62$; $p < 0.01$), with the Hansen test not rejecting the validity of the instruments ($p = 0.284$) and the Arellano–Bond test showing no second-order autocorrelation ($p = 0.417$). The exclusion of the five enterprises of the fifth maturity level, which might exert leverage, reduces the coefficient only marginally ($\beta = 20.18$; $p < 0.01$).

On the basis of the identified constraints a six-stage roadmap has been elaborated (Figure 7 and Table 10). Its distinguishing feature, following from the results of section 4.4, is the priority of the data infrastructure over the artificial intelligence services: the pilot AI stage begins only after the customer data platform has entered operation.

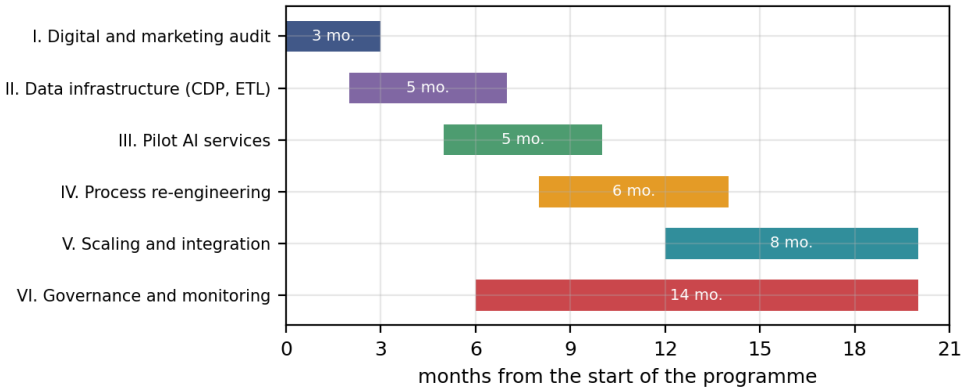


Figure 7. Roadmap of the implementation of the AI-driven innovative marketing management system (developed by the author)

Table 10. Stages of implementation, resource requirements and exit criteria

Stage	Key works	Duration, months	Cost, % of annual revenue	Exit criterion
I. Digital and marketing audit	Assessment of DMI, mapping of data flows and processes, benchmarking	3	0.10–0.15	DMI measured; constraint identified
II. Data infrastructure	ETL pipelines, customer data	5	0.90–1.40	≥ 85 % of transactions

Stage	Key works	Duration, months	Cost, % of annual revenue	Exit criterion
	platform, data quality rules, unified profile			in the unified profile
III. Pilot AI services	Demand forecasting and segmentation on two to three categories	5	0.45–0.70	MAPE ≤ 12 % on the pilot categories
IV. Process re-engineering	Embedding of predictions into planning, experimentation routine, roles	6	0.60–0.90	≥ 60 % of decisions analytics-based
V. Scaling and integration	Extension to the full assortment, pricing and recommendation engines	8	0.55–0.85	ROMI growth ≥ 40 % against the base year
VI. Governance and monitoring	KPI system, privacy and security, model monitoring, retraining	14 (parallel)	0.20–0.30	Model drift controlled; audit passed
Total programme	—	20	2.80–4.10	Movement of at least one maturity level

Source: developed by the author on the basis of the experience of eleven pilot enterprises.

The barriers that have to be overcome in the course of the programme were ranked by the method of expert assessment; the results are presented in Table 11. The concordance coefficient of 0.734 confirms the consistency of the expert opinions.

Table 11. Ranking of the barriers to the implementation of digital platforms and AI technologies in marketing (n = 144)

Barrier	Average score (1–10)	Rank	Critical for enterprises, %	Predominantly affected size group
Fragmentation and low quality of data	8.61	1	74.3	All groups
Shortage of data-analytical competences	8.34	2	70.8	Medium and small
Cost of platform infrastructure and licences	7.92	3	64.6	Small
Resistance of processes and managerial habits	7.48	4	58.3	Large and medium

Absence of a measurement and KPI system	6.87	5	51.4	All groups
Concerns about data privacy and security	6.14	6	43.1	Large
Dependence on external platform intermediaries	5.76	7	38.9	Small and medium
Unclear legal status of algorithmic decisions	5.23	8	31.9	Large

Source: author's survey; Kendall's coefficient of concordance W = 0.734, significant at p < 0.01.

The scenario projection to 2030 is presented in Figure 8 and Table 12. Under the baseline scenario the average maturity index of the enterprises of the sample reaches 3.25 points by 2030 and the return on marketing investment reaches 183 %; under the optimistic scenario the corresponding values are 3.88 points and 238 %. The inertial scenario, in which enterprises continue to acquire technologies without integrating data and redesigning processes, yields only 2.71 points and 137 %.

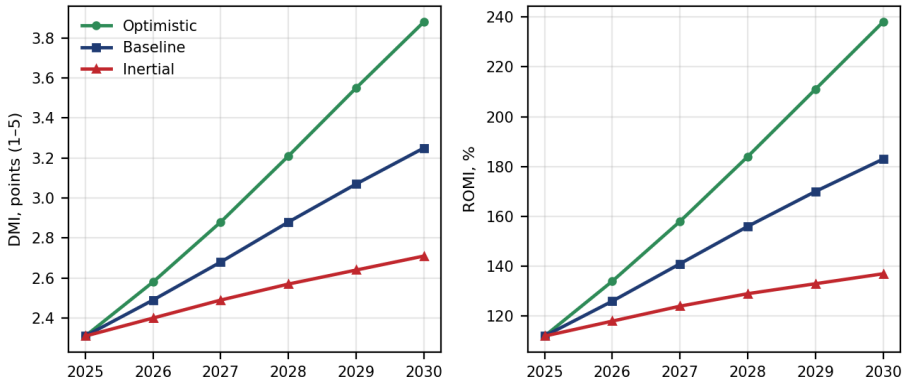


Figure 8. Scenario projection of the digital marketing maturity index and of the return on marketing investment, 2025–2030 (author's calculations)

Table 12. Quantitative parameters of the scenarios of development of AI-driven innovative marketing up to 2030

Indicator	2025 (base)	Inertial 2030	Baseline 2030	Optimistic 2030
Digital marketing maturity index, points	2.31	2.71	3.25	3.88
Return on marketing investment, %	112	137	183	238
Commercialisation cycle, months	12.6	11.8	10.8	9.6
Share of new products in revenue, %	12.1	14.0	16.5	19.5
Enterprises at levels L4–L5, %	19.4	26.8	41.3	58.7
Enterprises using AI in forecasting, %	18.3	27.5	44.1	63.2

Average forecast error (MAPE), %	22.4	18.6	13.2	9.1
Additional value added, bln UZS (sample)	—	342	914	1 587

Source: author's calculations on the basis of the estimated panel coefficients and the calibrated trajectories of the maturity index.

The results obtained permit several substantive observations that go beyond the confirmation of the general proposition that digitalisation is beneficial.

First, the study identifies an inversion between the ease of adoption and the economic value of artificial intelligence use cases. The applications that require the least data integration content generation and conversational agents are adopted three to four times more frequently than the applications with the highest measured effect. This inversion explains a considerable part of the productivity paradox observed at the level of the individual enterprise: aggregate expenditure on artificial intelligence grows, but it is concentrated in the applications with the lowest marginal return. The managerial implication is that the sequence of implementation matters more than the volume of investment, and the roadmap proposed in section 4.7 is constructed precisely to correct this sequence.

Second, the econometric results indicate that the effect of digital maturity operates through three distinct channels. The efficiency channel is expressed in the growth of the return on marketing investment, the speed channel in the shortening of the commercialisation cycle and the renewal channel in the growth of the share of new products. The presence of the second and the third channels is theoretically important, since it shows that digital platforms and artificial intelligence influence not only the cost of marketing operations but also the innovative capability of the enterprise as such. This finding supports the interpretation of digital maturity as a dynamic capability in the sense of D. Teece rather than as an ordinary operational resource.

Third, the comparison of forecasting methods yields a result of practical significance for enterprises with limited budgets. The largest single improvement in accuracy from 24.7 % to 15.4 % of error is achieved by the mere transition from expert judgement to a classical statistical model, which requires a modest investment. The subsequent transitions to machine learning and to ensembles produce smaller improvements at rapidly rising cost. For the majority of medium-sized enterprises of Uzbekistan the rational strategy is therefore not to reproduce the technological frontier but to occupy the point of the highest marginal return, which the present computations locate at the level of gradient boosting.

Fourth, the finding that the share of staff with data-analytical competences exerts an effect comparable to half a maturity level supports the argument that policies of digital transformation should be balanced between capital expenditure and human capital. The prevailing practice of subsidising equipment and licences while leaving the formation of competences to the enterprises themselves is, in the light of these estimates, suboptimal.

Fifth, the asymmetry of data ownership documented in Table 2 raises a strategic question that extends beyond the individual firm. Enterprises that operate predominantly through external marketplaces obtain access to demand but not to the data trace of that demand, which reproduces at the level of the digital economy the classic problem of the loss of the customer relationship by the contract manufacturer. In the long run this asymmetry may limit the innovative capability of the national producer, and it therefore constitutes a legitimate object of regulatory attention, for instance in the form of requirements of data portability.

The limitations of the study should be stated explicitly. The sample, although reasonably large, is confined to four regions and to the manufacturing and wholesale

sectors, so the extension of the conclusions to services requires additional verification. The digital marketing maturity index relies partly on self-reported data, which introduces the possibility of an optimistic bias, although the anchoring of each item to observable practices was designed to limit it. The panel covers five years, which is sufficient for the estimation of within-firm effects but short for the identification of long-run dynamics. Finally, the computational experiment was conducted on eleven enterprises; a wider replication, particularly in sectors with longer product cycles, is a natural direction of further work. Future research should also address the question of the durability of the advantages obtained through artificial intelligence, given that the underlying models are increasingly commoditised and that the source of differentiation shifts towards proprietary data and organisational routines.

Proposals

On the basis of these results the following proposals are formulated.

1. At the level of the enterprise, to adopt the sequence of implementation established by the roadmap of Table 10, in which the construction of the unified customer data platform precedes the deployment of artificial intelligence services, and to fix the movement of at least one maturity level within twenty months as the target of the programme, with an expenditure of 2.8–4.1 % of annual revenue.
2. To introduce into the internal management reporting of enterprises a quarterly measurement of the digital marketing maturity index together with the three performance indicators used in this study, so that the progress of the programme is monitored by outcomes rather than by the volume of expenditure.
3. At the level of sectoral ministries, to include the digital marketing maturity index in the system of monitoring of industrial development programmes and to set the target of raising the share of enterprises at the fourth and fifth levels to 41 % by 2030, corresponding to the baseline scenario of Table 12.
4. To reorient a part of the instruments of state support from the subsidising of equipment and licences towards the co-financing of data infrastructure and of the training of data-analytical personnel, since the estimated effect of competences is comparable to that of half a maturity level and the competence barrier ranks second in the hierarchy of obstacles.
5. To establish, on the basis of higher education institutions of the regions, applied training programmes in marketing analytics and machine learning oriented towards the practical tasks of enterprises, with the participation of enterprises in the formation of the curricula and with project-based final work performed on the enterprises' own data.
6. To examine, at the level of regulation, the introduction of requirements of data portability for digital platforms operating in the national market, so that enterprises trading through marketplaces retain access to the data trace of their own transactions, which constitutes the raw material of innovative marketing.
7. To develop a national methodological guideline for the assessment of the effectiveness of artificial intelligence projects in marketing, including the mandatory comparison against a simple benchmark, which would prevent the acquisition of complex solutions where a simpler configuration attains a comparable result at a fraction of the cost.

4. Conclusions

The study has developed and empirically substantiated an approach to improving the management of innovative marketing processes at enterprises on the basis of digital platforms and artificial intelligence technologies. The principal conclusions are the following. A six-layer architecture of the AI-driven innovative marketing management system has been proposed, in which the layer of marketing processes occupies the central position and the technological layers serve it rather than the reverse. The empirical analysis identifies the binding constraint of the system in the platform and data layer for

62.5 % of the enterprises and in the competence layer for 29.9 %, while the layer of artificial intelligence services is practically never the constraint. A digital marketing maturity index has been constructed on five weighted dimensions and validated on a sample of 144 enterprises. The average value of the index is 2.31 points on a five-point scale; 52.8 % of enterprises remain at the first two levels, and only 3.4 % have attained the highest level. The differentiation of economic performance across the levels is monotonic and substantial. The panel estimation establishes that a movement of one maturity level raises the return on marketing investment by 21.4 percentage points, shortens the commercialisation cycle by 1.9 months and increases the share of new products in revenue by 4.7 percentage points; each artificial intelligence use case in regular operation adds 6.8 percentage points of ROMI. The computational experiment demonstrates that machine learning reduces the demand forecasting error from 24.7 % to 8.4 %, with the economically rational configuration for a medium-sized enterprise located at the level of gradient boosting.

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