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A MULTILEVEL MODEL OF ARTIFICIAL INTELLIGENCE ADOPTION IN ENTERPRISE MARKETING: AN ECONOMETRIC ANALYSIS OF THE EFFECT UNDER UKRAINIAN MARKET CONDITIONS

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Koberniuk S. O. A Multilevel Model of Artificial Intelligence Adoption in Enterprise Marketing: An Econometric Analysis of the Effect Under Ukrainian Market Conditions

The aim of the study is to develop a multilevel model of artificial intelligence adoption in enterprise marketing that combines an original typology of maturity levels, an econometric substantiation of the dependence of the economic effect on the level of implementation, and a forecast of the Ukrainian market structure through 2030. The methodological basis comprises systemic and comparative analysis, econometric modeling, and multi-source triangulation of empirical data drawn from the AI Focus 2026 study (216 Ukrainian enterprises), the Boston Consulting Group (1.250 executives) and PwC (4.454 executives) reports, and statistics from Stanford HAI and Eurostat. A four-level maturity scale is proposed – fragmentary, functional, integrated, and transformational – aligned with leading international frameworks and adapted to marketing specifics. The integrated economic effect index rises from 0.148 at the fragmentary level to 0.684 at the integrated level, while the decay of the marginal increment reveals the logistic rather than exponential nature of the process. The gap between the extreme levels in the share of enterprises reporting a significant positive effect reaches 10.6 times. Triangulation across a combined sample of about 5.920 enterprises confirms the robustness of the maturity–outcome relationship, with an advantage coefficient from 1.4 to 10.6, interpreted as a self-reinforcing cycle of capability accumulation. The calibrated logistic model forecasts the global share of mature enterprises approaching 78% by 2030, with the Ukrainian market following the same trajectory at a lag of about one year. The barrier transition coefficient (0.662) quantifies a high threshold of movement between levels dominated by technological and economic obstacles. The practical value consists in providing enterprises with a measurable self-assessment apparatus and in substantiating the priority of investment in tool integration over their mere accumulation. It makes sense to focus further research on industry verification of the model and refining the parameters of the transformational level.

Keywords: artificial intelligence; marketing; adoption maturity; econometric modeling; logistic curve; economic effect; implementation barriers; digital transformation.

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**Кобернюк С. О. Багаторівнева модель адопції штучного інтелекту в маркетинговій діяльності підприємств:
економетричний аналіз ефекту в умовах українського ринку**

Метою дослідження є розроблення багаторівневої моделі адопції штучного інтелекту в маркетинговій діяльності підприємств, яка поєднує авторську типологію рівнів зрілості, економетричне обґрунтування залежності економічного ефекту від рівня впровадження та прогнозування структури українського ринку на горизонт 2030 р. Методологічну основу становлять системний і порівняльний аналіз, економетричне моделювання та багатоджерельна триангуляція емпіричних даних. Емпірична база охоплює дослідження AI Focus 2026 (216 українських підприємств), звіти Boston Consulting Group (1 250 керівників), PwC (4 454 керівники), а також статистику Stanford HAI та Eurostat. Запропоновано чотирирівневу шкалу зрілості – фрагментарний, функціональний, інтегрований та трансформаційний рівні – узгоджену з провідними міжнародними рамками й адаптовану до маркетингової специфіки. Розраховано інтегральний індекс економічного ефекту, який зростає від 0,148 на фрагментарному рівні до 0,684 на інтегрованому, причому згасання граничного приросту засвідчує логістичну природу процесу. Розрив між крайніми рівнями за часткою підприємств зі значним позитивним ефектом сягає 10,6 раза. Багатоджерельна триангуляція на сукупній вибірці близько 5 920 підприємств підтвердила стійкість залежності «зрілість – результат» з коефіцієнтом переваги від 1,4 до 10,6, що інтерпретується як вияв самопідсилювального циклу накопичення спроможностей. Логістична модель адопції, калібрована на реальних часових точках, прогнозує зростання світової частки зрілих підприємств до приблизно 78 % до 2030 р.; український ринок рухається тією самою траєкторією з відставанням приблизно на 1 рік. Обчислено бар'єрний коефіцієнт переходу (0,662), що відображає високий поріг руху між рівнями з домінуванням технологічних та економічних перешкод. Практична цінність роботи полягає в наданні підприємствам вимірюваного апарату самооцінки та обґрунтуванні пріоритетності інвестицій у інтеграцію інструментів над їх простим накопиченням. Подальші дослідження доцільно зосередити на галузевій верифікації моделі та уточненні параметрів трансформаційного рівня.

Ключові слова: штучний інтелект; маркетинг; зрілість адопції; економетричне моделювання; логістична крива; економічний ефект; бар'єри впровадження; цифрова трансформація.

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INTRODUCTION

The global artificial intelligence (AI) market expands at an unprecedented pace. The average annual growth of private investment in these technologies over 2013–2025 reached 46.5%, and in 2025 their volume hit a record 344.7 billion USD, up 128.6% year on year [1]. Organisational deployment of intelligent tools has spread to 88% of companies worldwide, with productivity gains in marketing teams from generative models reaching 72% [2]. Marketing together with sales consistently ranks among the functions with the highest value-creation potential, which makes this domain a priority area of the intelligent transformation of business.

The spread of the technology outruns its financial return, and this gap remains the key unresolved problem. Only 12% of companies have simultaneously achieved revenue growth and cost reduction from AI, whereas 56% report no tangible financial effect; organisations with a mature technological foundation obtain a substantial return three times more often [3]. European statistics confirm the unevenness of the process: intelligent technologies are used by only 20% of EU enterprises, with a range from 5.2% to 42% depending on the country [4].

The Ukrainian market stands out for its high declared engagement – 93.1% of companies already

use AI or plan to develop its use – yet the transition from experiments to a systemic effect proceeds slowly [1]. This mismatch between the scale of deployment and the quality of the outcome indicates that the decisive factor is not the fact of tool use as such but the level of maturity of their integration into business processes.

Earlier studies laid the structural foundation of this line of research – the architecture of integrated AI-based marketing systems and a comprehensive system of metrics for monitoring their effectiveness [5; 6]. The logical continuation is a dynamic model that describes an enterprise's transition between maturity levels and quantifies the dependence of the economic effect on the level attained.

LITERATURE REVIEW

The theoretical basis for studying technology diffusion remains the theory of innovation diffusion, which describes adoption through successive categories of adopters and accounts for the S-shaped form of the adoption curve [7]. This framework sets the logic of the uneven, stage-based character of technological change. At the same time it was formed to describe a single act of product adoption, whereas intelligent tools require the prolonged accumulation of organisational capability and therefore call for a revision of the classical model toward stages of maturity.

Contemporary applied research closes this gap through the maturity concept. A four-stage model of corporate AI maturity has been proposed, in which an enterprise's financial indicators improve consistently with the transition to higher stages [8]. A comparable four-level scale underpins a study of 1,250 executives, which records a twofold advantage of mature companies in revenue growth rates [9].

The concentration of the effect within a narrow group of the most mature companies is a recurring motif of industry analytics: amid the spread of AI across the majority of organisations, only about 6% of them achieve a tangible impact on operating profit [10]. The maturity approach is acquiring the status of a dominant research framework. Yet the available models are largely descriptive – they record the dependence of the effect on the stage but do not offer its quantitative expression suitable for forecasting and practical application.

AI in marketing has been addressed systematically in the international literature. A systematic review of more than five hundred publications from 2015-2023 outlined the principal directions – personalisation, predictive analytics, and the automation of communications [11]. A distinct body of work is devoted to intelligent conversational agents as a tool of marketing interaction [12]. These studies form a functional map of applications but largely abstract from the question of economic efficiency and the stage-based character of implementation.

Ukrainian scholarship actively develops this topic. A model of an enterprise AI implementation strategy has been proposed, and the challenges and opportunities of intelligent technologies for business have been systematised [13; 14]. The integration of digital tools into marketing processes and the attendant implementation barriers have been examined [15], as have the directions of AI application in digital marketing and social media [16; 17]. Separate works generalise cases of AI use by Ukrainian companies and the sectoral specifics of digital marketing in Ukraine [18; 20].

Despite the substance of these studies, the quantitative modelling of the relationship between the level of adoption maturity and the economic effect on a verified empirical base remains outside researchers' attention. Filling this gap defines the research niche and the direction of the present work.

AIM, RESEARCH QUESTIONS AND HYPOTHESES

The aim of the study is to develop a multilevel model of AI adoption in enterprise marketing that combines an original typology of maturity levels, an econometric justification of the dependence of the

economic effect on the level of implementation, and a forecast of the Ukrainian market structure through 2030 on a verified empirical base.

The study is guided by three research questions. The first asks whether the economic effect of AI in marketing depends on the level of adoption maturity rather than on the fact of use as such. The second concerns the functional form of the maturity-effect relationship and whether it indicates saturation. The third addresses the adoption trajectory and the 2030 market structure that Ukraine follows relative to the global one.

Three hypotheses are tested accordingly. The first (H1) states that the integrated economic effect increases monotonically with the maturity level, with a decaying marginal increment that indicates a logistic rather than an exponential process. The second (H2) holds that the maturity–outcome relationship is robust across independent samples and markets, which points to a self-reinforcing mechanism rather than a sampling artefact. The third (H3) maintains that the transition between levels is constrained by a measurable barrier threshold dominated by technological and economic obstacles.

Achieving the aim entails generalising theoretical approaches to modelling technology adoption; developing a four-level maturity scale with a justification of transition criteria; building an econometric model of the dependence of the probability of a significant effect on the level of implementation; determining the integrated barrier transition coefficient; forming a forecast of the enterprise structure by adoption level through 2030; and developing practical recommendations for the transition to higher maturity levels.

METHODS

The methodological design combines systemic and comparative analysis, econometric modelling, and multi-source triangulation. The classical theory of innovation diffusion treats adoption as a one-off transition of an agent from the state of «does not use» to the state of «uses» [7]. For intelligent tools this dichotomy loses explanatory power: an enterprise may formally apply generative models without obtaining a measurable result. The depth of integration of the technology into marketing processes becomes decisive, which requires replacing the binary logic of adoption with a continuum of maturity.

The proposed model treats AI adoption as the sequential passage through four levels, each differing in the character of tool use, organisational provision, and attainable economic effect. The first three levels are empirically calibrated on data from a study of

Ukrainian business [1]; the fourth describes a target state whose parameters are established through the forecast saturation of the adoption curve and verified

against the indicators of leading companies from independent sources [3; 9]. The structure of the scale is given in Table 1.

Table 1

Four-level scale of AI adoption maturity in marketing

Level	Name	Character of AI use	Organisational provision	Share, %
L1	Fragmentary	Episodic use of individual tools without a strategy	Employee initiative, no budget or metrics	25.0
L2	Functional	Regular use in separate marketing processes	Responsible persons, budget within the function	29.2
L3	Integrated	Embedding into end-to-end processes, integration with CRM/BI	Cross-functional coordination, KPI system	38.9
L4	Transformational	AI defines the marketing business model, autonomous agents	Strategic ownership, continuous optimisation	forecast

Source: compiled by the author; the distribution of enterprises is from [1].

The empirical base comprises four independent sources. The AI Focus 2026 study covers 216 Ukrainian enterprises and provides the primary distribution of enterprises by maturity level and by the character of the economic effect [1]. The Boston Consulting Group report (1,250 executives) and the PwC survey (4,454 executives) supply cross-market benchmarks of the leaders' advantage [3; 9]. Statistics from Stanford HAI and Eurostat frame the investment dynamics and the cross-country breadth of adoption [2; 4]. The combined sample of about 5,920 enterprises underpins the triangulation, whose purpose is to establish whether the maturity–outcome relationship reproduces across heterogeneous samples and methodologies rather than being an artefact of a single dataset.

Three model specifications are introduced. The integrated economic effect index (IEE) collapses the distribution of companies by the character of the effect into a single indicator. Each response category is assigned a weight reflecting its contribution to the result, after which the weighted sum is normalised by the share of definite responses:

$$IEE = \frac{1.0 \cdot a + 0.5 \cdot b + 0.1 \cdot c + 0.0 \cdot d}{a + b + c + d}, \quad (1)$$

where a, b, c, d are the shares of enterprises reporting, respectively, a significant positive, moderate positive, minor, and absent economic effect; the «hard to answer» and «other» categories are excluded from the normalisation.

To verify that the relationship is not an artefact of a single sample, the maturity premium (MP) is introduced as the ratio of the target indicator for mature enterprises to its value for less mature ones:

$$MP = \frac{X(\text{mature})}{X(\text{less mature})}. \quad (2)$$

The dynamics of adoption are described by a logistic function that captures the initial acceleration, the inflection point, and saturation:

$$A(t) = \frac{K}{1 + e^{-r(t - t_0)}}. \quad (3)$$

where $A(t)$ is the share of enterprises that have reached the integrated level (L3 and above) at time t ; K is the limiting share (the saturation asymptote); r is the adoption rate; and t_0 is the year of the inflection point.

The barrier transition coefficient (BTC) quantifies the intensity of the obstacles that restrain movement along the S-curve as the normalised weighted value of the shares of enterprises facing substantial obstacles:

$$BTC = \sum (b_i - w_i). \quad (4)$$

where b_i is the share of enterprises that named the i -th barrier (in unit fractions) and w_i is the barrier weight (with equal weights $w_i = 0.25$).

The calculations were performed in a spreadsheet environment; the logistic parameters were calibrated on real temporal observations rather than fitted to a single cross-section.

RESULTS AND DISCUSSION

Integrated economic effect and the maturity premium. The distribution of companies by the character of the effect, converted into the IEE by formula (1), is presented in Table 2.

The index grows monotonically ($0.148 \rightarrow 0.444 \rightarrow 0.684$), yet the growth rate decays: the L1 $\rightarrow$ L2 transition triples the index ($\times 3.01$), whereas L2 $\rightarrow$ L3 raises it only 1.54-fold. The decay of the marginal increment is a direct empirical sign of approaching saturation, which justifies the use of a logistic rather than an expo-

Table 2

Calculation of the integrated economic effect index by maturity level

Level	a (signif.)	b (moder.)	c (minor)	d (none)	Weighted sum	Base	IEE
L1	3.7	9.3	31.5	33.3	11.50	77.8	0.148
L2	11.1	52.4	7.9	14.3	38.09	85.7	0.444
L3	39.3	34.5	4.8	4.8	57.03	83.4	0.684

Source: calculated by the author from [1].

nential function at the subsequent modelling stage and confirms hypothesis H1. A graphical interpretation of the scale with the accumulation of the economic effect as maturity grows is given in Figure 1.

To ensure that the detected relationship is not an artefact of a single sample, the maturity premium computed by formula (2) across independent sources is given in Table 3.

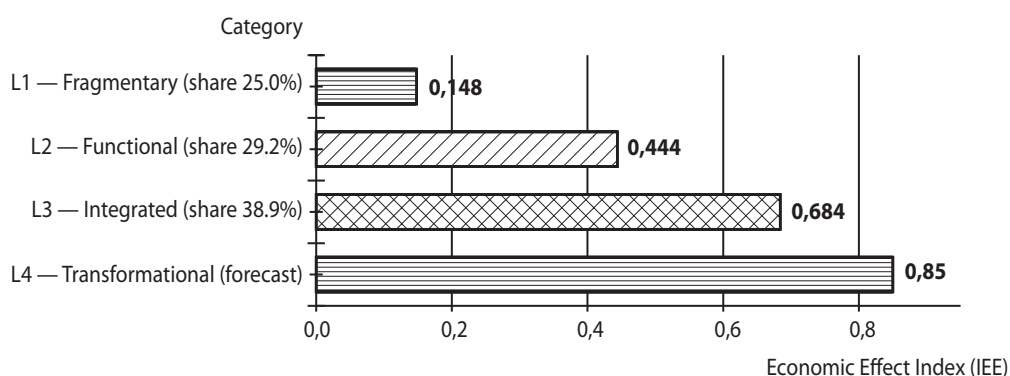


Fig. 1. Four-level scale of AI adoption maturity in marketing

Source: constructed by the author; the IEE values are calculated from [1].

Table 3

Maturity premium by independent sources

Indicator of the leaders' advantage	AI Focus [1]	BCG [9]	PwC [3]
Share with a significant (substantial) effect	10.6	–	3.0
Revenue growth	–	1.7	2.3
Cost reduction	–	1.4	1.7
EBIT margin	–	1.6	~1.3

Source: calculated by the author from [1; 3; 9].

Three independent samples with a combined size of about 5,920 enterprises (216 + 1,250 + 4,454) record the same direction: mature enterprises outperform less mature ones across all financial metrics with a coefficient from 1.4 to 10.6. The convergence of estimates obtained on different markets and by different methodologies allows the “maturity level → economic effect” relationship to be treated not as a statistical accident but as a stable regularity with a causal mechanism: the reinvestment of early returns into the further development of capabilities forms a self-reinforcing cycle, which supports hypothesis H2 [9].

Logistic adoption dynamics and the forecast through 2030. The decay of the marginal IEE increment points to the logistic character of the process;

the spread of mature practices is described by the S-shaped function (3). The parameters are calibrated on real temporal observations: the global share of mature companies rose from 26% in 2024 to 40% in 2025 [9], while the Ukrainian advanced-level indicator stood at 38.9% in 2026 [1]. Setting the limiting share $K = 80\%$ – the level at which intelligent tools become an industry norm for the majority of enterprises – and locating the inflection of the global trajectory at 2025 yields $r = 0.731$ and $t_0 = 2025$. The adoption trajectories with the forecast are shown in Figure 2.

The model forecasts the growth of the global share of mature enterprises to approximately 78% by 2030. The Ukrainian indicator of 38.9% in 2026 corresponds to the global level of late 2024-early 2025,

Share of mature enterprises (L3+), %

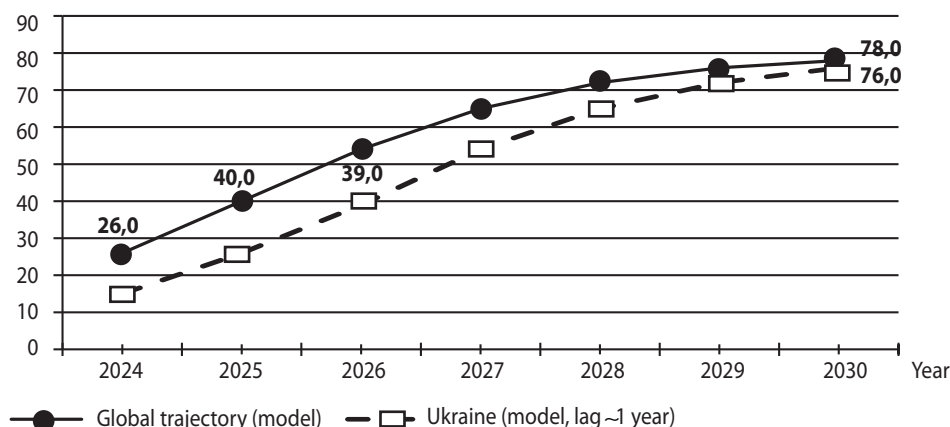


Fig. 2. Logistic trajectory of AI adoption with a forecast through 2030

Source: constructed by the author; calibration from [1; 9].

which means a lag of about one year while the same movement trajectory is preserved. If the current pace holds, the share of Ukrainian enterprises at the integrated level will reach about 76% by 2030, which answers the third research question. The adoption rate $r = 0.731$ corresponds to a doubling period of mature practices of roughly one year on the ascending part of the curve, consistent with the unprecedented pace of investment in the sector [2].

The forecast redistribution of the marketing effect follows directly from this dynamics: since the significant positive effect concentrates at the higher maturity levels, increasing the share of integrated enterprises implies a multiple growth of the market's aggregate return from intelligent tools. The contrast of the effect across levels is shown in Figure 3.

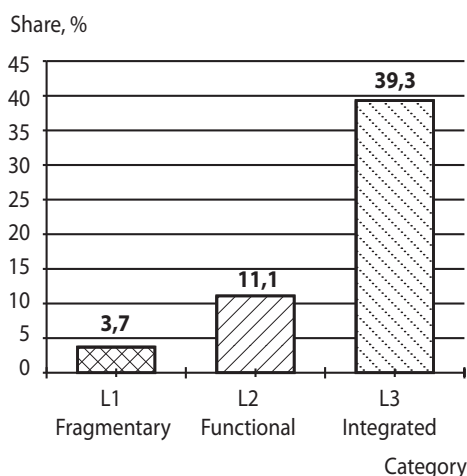


Fig. 3. Share of enterprises with a significant positive effect by maturity level

Source: constructed by the author from [1].

The gap between the extreme levels reaches 10.6 times: the transition from fragmentary to integrated use raises the share of enterprises with a significant effect from 3.7% to 39.3%. This quantitatively confirms the thesis that economic return is created not by the fact of applying intelligent tools as such but by the depth of their integration into marketing processes, which provides an affirmative answer to the first research question.

Barrier transition coefficient. The transition of an enterprise to a higher maturity level is restrained by a set of barriers whose intensity determines the pace of movement along the S-curve. Their structure and the coefficient computed by formula (4) are given in Table 4.

The value $BTC = 0.662$ indicates a high transition threshold: on average about two-thirds of enterprises encounter each of the leading barriers. Obstacles of a technological and economic nature dominate – the complexity of integration with existing systems (73.6%) and the high cost of implementation (71.8%) – whereas organisational unreadiness plays a smaller though still substantial role (55.6%). The shortage of qualified specialists (63.9%) also appears as a leading obstacle in global studies [10; 19], which points to a universal rather than a purely national character of the personnel deficit and supports hypothesis H3. The barrier profile is shown in Figure 4.

A comparison of two indicators provides indirect confirmation of the model's causal mechanism: the share of enterprises that encountered no barriers (35.6%) is close to the share of advanced-level enterprises (38.9%). The attainment of the integrated maturity level is accompanied by the overcoming of key obstacles, which is consistent with the logic of the

Table 4

Structure of adoption barriers and calculation of the transition coefficient

Barrier type	Specific barrier	Share, %
Technological	Complexity of integration with existing systems	73.6
Economic	High cost of implementation	71.8
Technological	Shortage of specialists or technical expertise	63.9
Organisational	Business unreadiness due to low digitalisation	55.6
–	Integrated coefficient BTC	0.662

Source: calculated by the author from [1].

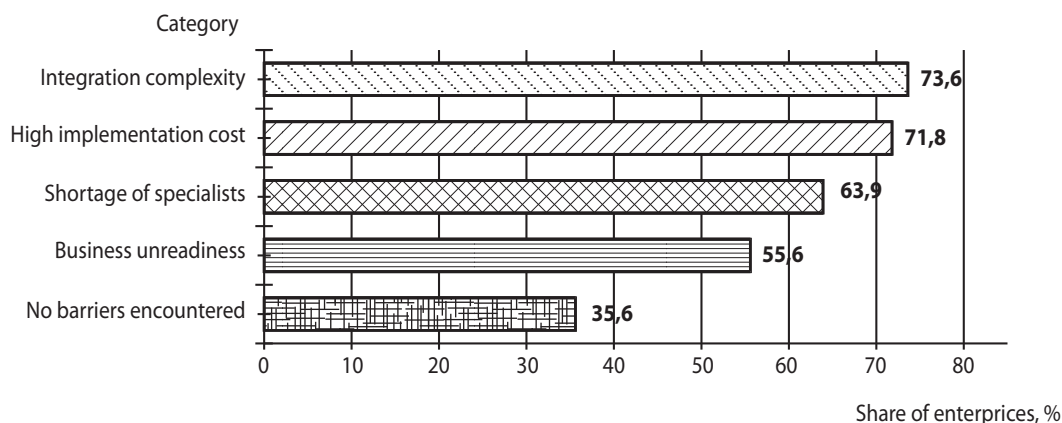


Fig. 4. Profile of AI adoption barriers in marketing

Source: constructed by the author from [1].

self-reinforcing cycle. The passability potential, computed as the complement of the coefficient ($1 - BTC = 0.338$), delineates the reserve of enterprises capable of transition provided that technological and financial constraints are removed in a targeted manner.

DISCUSSION AND LIMITATIONS

The findings align with the industry observation that a tangible operating-profit impact is reached by only a narrow group of the most mature companies [10], and extend it by giving the maturity–effect relationship a quantitative form and by verifying it through independent-source triangulation. A comparison with the descriptive maturity models [8; 9] shows that the proposed apparatus adds a calculable index and a calibrated adoption curve, moving from the statement of a dependence to its measurement and forecasting.

The study has several limitations. The data are cross-sectional rather than longitudinal, so the causal mechanism is inferred from the convergence of independent estimates rather than proven directly. The parameters of the transformational level (L4) rest on the forecast saturation of the curve rather than on observed values, since a representative mass of L4 enterprises has not yet formed. Triangulation combines samples of different sizes and methodologies,

which yields a directional convergence rather than a pooled statistical estimate. The Ukrainian base rests on a moderate self-reported sample of 216 enterprises, which sets the boundary of generalisation and defines the direction of subsequent verification.

CONCLUSIONS

The study of AI adoption in marketing confirmed that the decisive factor of economic return is not the use of intelligent tools as such but the level of their integration into business processes. The proposed four-level maturity scale is consistent with leading international frameworks and at the same time adapted to marketing specifics, which allows it to be applied as a diagnostic instrument for positioning an enterprise and planning the transition to a higher level.

Quantitative modelling revealed the non-linear character of the dependence of the effect on maturity. The integrated economic effect index rises from 0.148 at the fragmentary level to 0.444 at the functional and 0.684 at the integrated level, and the decay of the marginal increment indicates a logistic rather than an exponential nature of the process. The gap between the extreme levels in the share of enterprises with a significant positive effect reaches 10.6 times.

The robustness of the detected regularity is ensured by multi-source triangulation. Three indepen-

dent samples with a combined size of about 5,920 enterprises, collected on different markets and by different methodologies, record the same direction of the maturity-outcome relationship with an advantage coefficient from 1.4 to 10.6. The convergence of estimates allows the relationship to be treated as a manifestation of a self-reinforcing cycle in which the reinvestment of early returns forms a cumulative advantage of mature enterprises.

The logistic adoption model, calibrated on real temporal points, forecasts the growth of the share of mature enterprises worldwide to approximately 78% by 2030. The Ukrainian market follows the same trajectory with a lag of about one year: the indicator of 38.9% in 2026 corresponds to the global level of late 2024, and if the current pace holds, the share of domestic enterprises at the integrated level will approach 76% by the end of the decade. This defines a strategic window of opportunity for an accelerated narrowing of the gap.

The barrier transition coefficient (0.662) quantitatively confirmed a high threshold of movement between levels dominated by obstacles of a technological and economic nature. The proximity of the share of enterprises without barriers to the share of advanced-level enterprises indirectly confirms that the attainment of maturity is accompanied by the overcoming of key constraints. The practical value of the work lies in providing enterprises with a measurable self-assessment apparatus and in substantiating the priority of investment in tool integration over their mere accumulation. Further research should focus on the sectoral verification of the model, above all in the agrarian sector, and on the refinement of the transformational-level parameters as longitudinal data on leading companies accumulate. ■

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During the preparation of this manuscript, generative artificial intelligence tools (Claude, Anthropic) were used solely as an auxiliary aid for translating individual complex domain-specific constructions from Ukrainian into English and for the linguistic

editing of certain technical formulations, in order to preserve terminological accuracy, the logic of exposition, and the meaning of the study. The conceptual design, research methodology, data analysis, interpretation of results, and formulation of conclusions belong to the author, who has reviewed and takes full responsibility for the entire content of the publication. AI tools are not listed as authors of the article.

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ЦИФРОВА ТРАНСФОРМАЦІЯ МАРКЕТИНГОВОЇ ДІЯЛЬНОСТІ ЯК ФАКТОР ПІДВИЩЕННЯ ЕФЕКТИВНОСТІ УПРАВЛІННЯ БІЗНЕСОМ В УМОВАХ СУЧАСНОГО ПРАВОВОГО РЕГУЛЮВАННЯ

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Ткачова Н. П., Ткачов М. М., Перерва П. Г. Цифрова трансформація маркетингової діяльності як фактор підвищення ефективності управління бізнесом в умовах сучасного правового регулювання

У статті досліджено особливості цифрової трансформації маркетингової діяльності як важливого чинника підвищення ефективності управління бізнесом в умовах сучасного правового регулювання. Обґрунтовано, що впровадження цифрових технологій, зокрема CRM-систем, Big Data, штучного інтелекту, цифрової реклами та платформ електронної комерції, забезпечує підвищення результативності маркетингових процесів, удосконалення механізмів прийняття управлінських рішень і формування додаткових конкурентних переваг підприємств. Проведено систематизацію основних напрямів впливу цифрових маркетингових інструментів на управлінську ефективність та визначено їх взаємозв'язок із сучасними вимогами правового регулювання у сферах захисту персональних даних, електронної комерції, цифрової реклами, інтелектуальної власності та кібербезпеки. Запропоновано інтегральний індекс ефективності цифрового маркетингу, який дає змогу комплексно оцінювати результати цифрової трансформації маркетингової діяльності з урахуванням економічних, управлінських і правових показників. Розроблено концептуальну модель цифрової трансформації маркетингової діяльності, що відображає взаємодію технологічних, маркетингових, управлінських і правових компонентів у єдиній системі управління бізнесом. На основі порівняльного аналізу встановлено позитивний вплив цифровізації маркетингової діяльності на конверсію маркетингових кампаній, рівень утримання клієнтів, швидкість прийняття управлінських рішень, рентабельність маркетингових інвестицій та задоволеність споживачів. Систематизовано основні правові ризики цифрового маркетингу та визначено механізми їх мінімізації шляхом впровадження комплаєнс-контролю, політик захисту даних, юридичного аудиту рекламної діяльності, заходів кібербезпеки та захисту прав інтелектуальної власності. Доведено, що ефективність цифрової трансформації маркетингової діяльності значною мірою залежить від рівня інтеграції цифрових інструментів із системою правового забезпечення підприємства. Практичне значення результатів дослідження полягає у можливості використання запропонованих методичних підходів для оцінювання ефективності цифрового маркетингу та формування стратегій цифрового розвитку підприємств.

Ключові слова: маркетинг; право; диджиталізація; моделі розвитку; управління підприємством; моделювання; інструменти маркетингу; управлінські рішення; інформаційне забезпечення; е-комерція; торгівля; підприємства.

Рис.: 1. **Табл.:** 3. **Формул.:** 1. **Бібл.:** 15.

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