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ECONOMETRIC MODELING OF THE INVESTMENT ATTRACTIVENESS OF IT PROJECTS USING LOGISTIC REGRESSION

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The purpose of this study is to develop an econometric toolkit for identifying and quantitatively assessing the factors influencing the probability of attracting external financing for IT projects in the context of the digital economy.

The methodological framework is based on econometric modeling techniques, in particular binary logistic regression (logit model), as well as system analysis, statistical data processing methods, and approaches to handling imbalanced datasets (reweighting and undersampling). Model validation was performed using the Wald test, likelihood ratio test, and the Hosmer-Lemeshow goodness-of-fit test.

Based on the modeling of a sample of Ukrainian IT projects, key determinants of successful fundraising were identified. The presence of early-stage investors was found to have a decisive impact, significantly increasing the likelihood of obtaining financing. A statistically significant positive effect of project commercial orientation and digital presence was established. Furthermore, a synergistic effect between technological innovation, particularly the use of artificial intelligence, and operational flexibility – manifested in reduced time-to-market – was substantiated.

The proposed approach can be applied as a decision-support tool in IT project management, particularly for assessing investment attractiveness, optimizing development strategies, and enhancing the efficiency of commercialization processes for innovative products. The practical significance of the developed models lies in their ability to provide IT managers and venture investors with an analytical toolkit for auditing initiatives at early stages, thereby minimizing the «valley of death» risks and optimizing financial resource allocation. The results contribute to risk reduction at the early stages of the project lifecycle and improve the robustness of managerial decision-making. Future research directions involve the use of recurrent neural networks to forecast the long-term evolutionary trajectories of IT products in a global digital market.

Keywords: IT project, IT product, digital economy, project management, logistic regression, optimization, modeling, investment attractiveness.

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STATEMENT OF THE PROBLEM IN GENERAL TERMS AND ITS CONNECTION WITH IMPORTANT SCIENTIFIC OR PRACTICAL TASKS

In the context of rapid development of the digital economy, the implementation of innovative IT projects is becoming a key driver of economic growth. However, the processes of developing and bringing new technological products to market are accompanied by an extremely high level of uncertainty and risk. Most technological initiatives cease to exist at early stages of the life cycle, primarily due to a lack of financial resources and errors in strategic planning.

Successfully overcoming these barriers critically depends on the ability of managers to optimally manage business processes. Accordingly, modeling and managing the processes of creating and developing IT projects requires a reliable toolkit for substantiating management decisions. Identifying and quantitatively assessing factors that signal to investors the potential viability of a project is an extremely important practical task. This allows optimizing the IT product development strategy, rationally allocating limited team resources, and increasing the probability of successful commercialization.

ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS ADDRESSING THIS PROBLEM AND APPROACHES TO ITS SOLUTION

The problem of assessing investment attractiveness and predicting the success of IT projects under conditions of high uncertainty in the digital economy is attracting increasing attention from the scientific community. Contemporary research in this area can be broadly divided into several interrelated directions, encompassing investment analysis, econometric modeling, and machine learning approaches.

The fundamental mechanisms of how venture capital makes decisions regarding the financing of technological initiatives are detailed in the work of P. A. Gompers et al. [1]. The authors demonstrate the priority of team and business model evaluation over the idea itself. The most dynamic direction is the integration of artificial intelligence and machine learning into project assessment processes. M. R. Bidgoli et al. [2] demonstrated the high effectiveness of applying machine learning approaches specifically for predicting the success of startups. For the quantitative prediction of project outcomes, data mining methods are widely applied, as substantiated in the research of A. Krishna et al. [3]. Meanwhile, S. Mseddi [4] investigated the dynamics of financing startups and impact investing, providing valuable regional evidence and comparative insights across MENA countries.

In the context of mathematical risk assessment tools, the methodology for proactive risk management and financial prediction using a stepwise logistic regression approach, as substantiated by D. Ait Lahcen and N.-E. Amghar [5], is of considerable interest. This approach enables effective work with dichotomous dependent variables, estimating the probability of a target event occurring, such as successfully attracting financing or avoiding financial failure. In their research [6], the authors addressed nonlinear modeling and focused on determining the optimal neural network parameters to predict the success of early-stage startups.

Despite the solid theoretical and methodological foundation [7-9], the analysis of existing publications indicates the fragmentation of current approaches. Most econometric models [5, 8] remain linear and are unable to fully account for the stochastic nature of digital markets, while powerful neural network and machine learning algorithms [2, 6] are often characterized by a low level of explainability and difficulty in interpreting results for real-world management. Furthermore, there is a lack of comprehensive studies that would adapt this toolkit specifically for the field of IT projects, taking into account the markers of the modern digital economy.

UNRESOLVED PARTS OF THE GENERAL PROBLEM TO WHICH THE ARTICLE IS DEVOTED

Despite the existing theoretical foundation, current approaches to assessing IT projects remain fragmented as most econometric models are linear and fail to account for the stochastic nature of digital markets. While machine learning and neural network algorithms offer high predictive power, they often suffer from low explainability, making them difficult to interpret for real-world management decisions. Furthermore, there is a lack of comprehensive studies specifically adapted for IT projects that integrate markers of the modern digital economy, such as the synergistic effect between technological innovation and operational flexibility. Methodologically, the problem of handling imbalanced datasets in the context of Ukrainian IT initiatives remains insufficiently addressed, necessitating a more robust approach to identifying the key determinants of investment attractiveness.

FORMULATION OF ARTICLE OBJECTIVES (PROBLEM STATEMENT)

The purpose of this study is to identify and quantitatively assess the key factors that influence the probability of obtaining external financing by domestic IT projects, based on econometric modeling methods.

To achieve this objective, the authors formed a representative sample of Ukrainian IT projects and selected a system of independent predictors to construct and verify logistic regression models, ultimately interpreting the derived parameters to formulate recommendations for substantiating

PRESENTATION OF THE MAIN RESEARCH MATERIAL WITH FULL SUBSTANTIATION OF THE SCIENTIFIC RESULTS OBTAINED

The analytical service Startup Ranking [10] was used as a source of empirical data, the purpose of which is to track growth signals of innovative companies. Within this study, IT products were chosen as the object of analysis as the most representative segment of the digital economy, characterized by a high level of innovativeness and investment activity and as a result of successful implementation of projects in the field of information technologies (IT project). Accordingly, a population of 176 Ukrainian IT projects was formed, among which 29 (approximately 17.4%) demonstrated the ability to successfully attract external financing, indicating their investment attractiveness and competitiveness.

Since the dependent variable (investment attraction result) is dichotomous, the use of the classical linear probability model is incorrect, as predicted values may fall outside the interval [0; 1]. Therefore, the logistic regression model (logit model) was chosen for modeling. The general form of the logistic distribution function defines the relationship between the probability of an event and the set of explanatory variables.

In order to deepen the analytical study, the relationships between the dependent variable (outcome) and the set of predictors (independent variables) were examined using econometric modeling methods, particularly logistic regression.

As the dependent variable in the model, a binary indicator of IT project financing availability was used: $Y = 1$ — if financing was attracted; $Y = 0$ — otherwise. Based on the preliminary log-linear analysis presented in [8], the following variables were selected as predictors: X_1 – source of initial financing (1 – presence of early investors/business angels, 0 – exclusively self-financing, bootstrapping); X_2 - strategic orientation of the project (1 – clear focus on profit generation and scaling, 0 – orientation toward other goals); X_3 – digital presence and social impact (1 – presence of an optimized website and active social media presence, 0 – passive online position); X_4 - key client segment (1 – orientation toward the B2B sector, 0 – other); X_5 – technological innovation factor (1 – integration of cutting-edge technologies, such as artificial intelligence (AI); 0 – standard solutions); X_6 – Time-to-Market speed factor (1 – Minimum Viable Product (MVP) development took less than 6 months; 0 – more than 6 months).

When constructing econometric models, various assumptions may be made regarding the nature of the relationship between the dependent variable Y_i, $i = 1, \dots, n$ (where n is the number of observations), and the vector of explanatory variables X_i, $i = 1, \dots, n$ (where k denotes the number of predictors in the model). If a conventional linear regression model is applied, the resulting specification is known as the linear probability model. However, this approach has several well-known limitations, the most important of which is that the predicted values of the dependent variable may fall outside the interval $[0; 1]$, which lacks a meaningful interpretation. To address this limitation in modeling probabilities, functions $F(\cdot)$ are employed whose range is confined to the interval $[0; 1]$: $P(Y = 1) = F(Z_i)$. The choice of the function $F(\cdot)$ determines the type of binary response model. Most commonly, either the cumulative distribution function of the standard normal distribution is used (resulting in a probit model) or the logistic distribution function (resulting in a logit model). For samples characterized by a relatively small variation in the explanatory variables, as in the present study, the qualitative conclusions derived from probit and logit models are typically very similar.

In what follows, we employ a logistic regression model, which can be represented as follows:

$$p_i = P(Y_i = 1) = \frac{1}{1+e^{-Z_i}} = \frac{e^{Z_i}}{1+e^{Z_i}} \tag{1}$$

The quantity Z_i may be interpreted as an unobservable (latent) variable that determines whether an IT project receives financing. Specifically, if: the quantity Z_i is greater than zero $Z_i > 0$, then the event occurs: $Y_i = 1$. Otherwise, if $Z_i < 0$, then the event does not occur: $Y_i = 0$.

Since p_i – denotes the probability that the i-th IT project receives financing, then $1 - p_i$ – represents the probability that it does not receive financing. Accordingly, the odds ratio of receiving to not receiving financing is given by $\frac{p_i}{1-p_i}$. In the logit model, the natural logarithm of the odds ratio (log-odds) is assumed to be a linear function of the explanatory variables:

$$\ln\left(\frac{p_i}{1-p_i}\right) = b_0 + b_1X_{1i} + b_2X_{2i} + \dots + b_mX_{mi} + \varepsilon_i$$

or

$$\frac{p_i}{1-p_i} = e^{b_0 + b_1X_{1i} + b_2X_{2i} + \dots + b_mX_{mi} + \varepsilon_i} \tag{2}$$

The last expression helps in the substantive interpretation of logit model parameters: for the j-th binary independent variable, the regression coefficient in exponential form e^{b_j} shows how much the odds ratio will change if the variable value equals 1.

The statistical software package Stata. The results of logit model estimation are presented in Tables 1, 2, 3. The tables shows the maximum likelihood estimates of parameters b_j, corresponding p-Wald statistic values ($p - level$) and the exponent values e^{b_j} of parameters b_j. Additionally, the tables presents summary statistics: the log-likelihood function value Log likelihood; the likelihood ratio value LR, the Hosmer-Lemeshow statistic value and corresponding p-values.

The variables included in the models were analyzed for multicollinearity using the tolerance indicator $1 - R_j^2$ (where R_j^2 - the squared multiple correlation coefficient of the j-th independent variable with all other predictors) and the indicator VIF, reciprocal to this value, which is called the variance inflation factor (VIF): $VIF = \frac{1}{1-R_j^2}$. In the presence of multicollinearity, the variable's tolerance approaches 0, and the value of the indicator VIF increases rapidly. It is considered that a value of this indicator exceeding 5 indicates the presence of multicollinearity. In all cases considered by us, the value of VIF did not exceed 2.5.

Table 1

Results of logit model 1 estimation based on the original data sample

Model factors X_j	Model 1		
	b_j	*p-level*	e^{b_j}
const	-5,52***	0,000	0,004
X_1	2,89***	0,000	18,0
X_2	1,40*	0,055	4,06
X_3	1,08*	0,076	2,96
X_4	0,60	0,360	1,83
X_5	0,82	0,156	2,28
$X_2 \cdot X_5$			
$X_3 \cdot X_5$			
$X_4 \cdot X_5$			
Log likelihood	-48,7		
LR statistic	56,8		
p-value for the LR statistic	0,000		
Hosmer-Lemeshow statistic	2,52		
p-value for the Hosmer-Lemeshow statistic	0,9607		

Source: developed by the authors

Analysis of Tables 1–3 demonstrates that, for all three models whose estimation results are reported, the values of the LR statistics exceed their corresponding critical values, while the associated p-values are below 0.001. This indicates that the ratio of the maximum value of the likelihood function for the unrestricted model to that for the restricted model is significantly greater than unity. In other words, for all three models, the null hypothesis of the joint insignificance of all coefficients (i.e., their simultaneous equality to zero) can be rejected at a significance level of less than 1%. Therefore, the models under consideration may be regarded as adequately fitting the observed data. It should also be noted that the LR statistic follows a χ^2 distribution and serves as an analogue of the F-statistic in linear regression models.

An additional diagnostic for assessing model adequacy is the Hosmer–Lemeshow χ^2 test. This goodness-of-fit measure evaluates how well the model corresponds to the observed data by comparing observed and expected frequencies of the outcome $y_i = 1$ (i.e., cases of receiving financing) across groups of observations. As shown in Tables 1–3, the p-values of the Hosmer–Lemeshow statistic for all estimated models exceed the critical threshold, which implies that there is no statistical basis to reject the null hypothesis of no difference between observed and expected frequencies. Consequently, the estimated models presented in Tables 1–3 can be considered adequately specified and well-fitted to the empirical data.

Let us now proceed to the interpretation of the obtained results. First, a logistic regression model (Model 1) was constructed, which included factors $X_1, \dots, X_5$, described above. As can be seen from Table 1, positive parameter estimates were obtained for all factors included in the model. Analysis of Model 1 estimation results shows that the greatest impact on receiving financing is exerted by factor X_1 – the presence of investors; this factor is significant at a significance level less than 0.001. Factors X_2, X_3 – the project's orientation toward profit generation and digital activity on the Internet (website presence and social media presence) also have a significant positive impact on the indicator. Meanwhile, the parameters for forvariables X_4, X_5 turned out to be positive but insignificant; therefore, we cannot consider the influence of these factors on the studied indicator as non-random.

The exponent values e^{b_j}, presented in Tables 1-3, show how the ratio of the odds of receiving financing to the odds of not receiving financing will change if factor X_j equals 1. As can be seen from Tables 1-3, in the presence of investors and all other conditions being equal, the odds ratio increases 18-fold; with the IT product's orientation toward profit generation – 4-fold; with the presence of a website and social media presence – almost 3-fold.

For Model 1, the following linear function was obtained Z_i:

$$\widehat{Z}_i = -5{,}52 + 3{,}00 \cdot X_{1i} + 1{,}40 \cdot X_{2i} + 1{,}08 \cdot X_{3i} + 0{,}60 \cdot X_{4i} + 0{,}82 \cdot X_{5i} \quad (3)$$

As noted above, the quantity Z can be regarded as a certain latent variable that determines the event of receiving financing. It is expected that an IT project receives financing if the value of this function is greater than zero. From formula (3), it can be seen that for IT projects whose MVP development took more than 6 months ($X_6 = 0$), financing is expected under the following conditions: the presence of early investors (X_1); strategic orientation of the project toward profit generation (X_2); digital presence and social impact (X_3). For IT projects that released their MVP within 6 months or less ($X_6 = 1$), financing is expected in the presence of investors and the fulfillment of at least two of the following conditions: orientation of the project toward profit (X_2); active digital presence (X_3); and if the key client segment is business (X_4).

To deepen the research, the impact of factor interactions on the Y indicator was analyzed. Model 2 (Table 2) included the base factors and a factor reflecting the interaction of factors X4 and X5. All coefficients in the model are positive and significant. As in Model 1, significant impact on the indicator is exerted by such factors as the presence of investors, the project's orientation toward profit, and active social media presence. The positive coefficient for the interaction factor means that the positive impact on receiving financing for IT projects with standard technological solutions ($X_5 = 0$) is substantially reinforced by the orientation of activities toward the B2B sector (X_4).

Table 2

Results of logit model 2 estimation based on the original data sample

Model factors X_j	Model 2		
	b_j	*p-level*	e^{b_j}
const	-5,06***	0,000	0,01
X_1	3,00***	0,000	20,1
X_2	1,37*	0,056	3,95
X_3	1,10*	0,059	3,01
X_4			
X_5			
$X_2 \cdot X_5$			
$X_3 \cdot X_5$			
$X_4 \cdot X_5$	1,20*	0,099	3,33
Log likelihood	-48,7		
LR statistic	56,8		
p-value for the LR statistic	0,000		
Hosmer-Lemeshow statistic	3,61		
p-value for the Hosmer-Lemeshow statistic	0,6073		

Source: developed by the authors

Model 3 (Table 3) accounts for the interaction of factors X_2 and X_5, as well as the interaction of factors X_3 and X_5. According to the obtained estimation results presented in Table 3, these factors have different effects on the Y indicator depending on the level of technological innovativeness of the IT project. Thus, commercial orientation toward profit exerts a significant positive impact on the Y indicator for IT projects without AI/ML integration ($X_5 = 0$). The presence of a website and social media presence (X_3) significantly increases the probability of receiving financing; however, for projects with standard solutions, this impact is somewhat less than for innovative IT projects with AI as Core Feature ($X_5 = 1$).

Thus, the constructed models show consistent results, according to which the factors influencing the receipt of financing by IT projects are, primarily, the presence of early investors, as well as the project's orientation toward profit generation and active digital presence. Furthermore, depending on the development speed and technology stack, a significant positive impact is exerted by such a factor as the orientation of the project's activities toward business.

Table 3

Results of logit model 3 estimation based on the original data sample

Model factors X_j	Model 3		
	b_j	*p-level*	e^{b_j}
const	-6,22***	0,000	0,00
X_1	3,14***	0,000	23,0
X_2			
X_3	3,24***	0,009	25,4
X_4	0,74	0,281	2,10
X_5			
$X_2 \cdot X_5$	3,26***	0,003	26,0
$X_3 \cdot X_5$	-2,75**	0,029	0,06
$X_4 \cdot X_5$			
Log likelihood	-44,4		
LR statistic	65,3		
p-value for the LR statistic	0,000		
Hosmer-Lemeshow statistic	3,26		
p-value for the Hosmer-Lemeshow statistic	0,8601		

Source: developed by the authors

It should be noted that in the studied sample, IT projects that received financing constitute only 17.4% of the total number of considered initiatives. Such a distribution of the dependent variable may lead to distortion of modeling results. The distribution can be changed using the thinning method or the sample reweighting method. To obtain a thinned sample, all cases of receiving financing were taken, and 58% of IT projects that did not receive financing were randomly selected. As a result of the transformation, the sample was reduced to 108 IT projects. Therefore, in our case, given the small sample size, the second strategy for forming the modeling sample — the reweighting method — is preferable. The results of constructing logistic regression models for the thinned and reweighted samples are presented in Table 4. As the comparative analysis shows, the results obtained for the original sample and the results obtained for the adjusted samples do not differ significantly.

To investigate the impact of factor X_6 (the Time-to-Market speed factor) on receiving financing, Model 4 was constructed, which included factors X_2, X_3, X_6 and also accounted for the interaction of factors X_4 and X_5. As a result of parameter estimation by the maximum likelihood method, the following model was obtained:

$$ln\left(\frac{p_i}{1-p_i}\right) = -2{,}84 + 1{,}22 \cdot X_{2i} + 1{,}47 \cdot X_{3i} - 1{,}04 \cdot X_{6i} + 1{,}38 \cdot X_{4i} \cdot X_{5i} \quad (4)$$

From the analysis of Model 4, it follows that the operational flexibility of the team is of critical importance for attracting capital by an IT project: the model coefficient for factor X_6 (Time-to-Market speed) proved to be positive and statistically significant. This indicates that, all other conditions being equal (strategic orientation, digital presence, and client segment), investors prefer dynamic IT projects that are capable of developing and releasing a minimum viable product (MVP) in less than 6 months. Rapid validation of ideas in the real market prevails over a prolonged development cycle.

The modeling results confirmed that for IT projects with a standard technology stack ($X_5 = 0$) or a longer development cycle ($X_6 = 0$), the primary orientation toward the B2B segment (factor X_4— key business clients) remains a significant success factor. The constructed logit models provide grounds to assert that high implementation speed (X_6, Time-to-Market) combined with an active digital strategy (X_3) are critically attractive factors for modern investors in the high-tech development segment. This proves the advantage of dynamic management models over conservative approaches to prolonged testing and formal technology protection, which is especially relevant for innovative products with AI integration.

Table 4

Model 4 parameter estimates obtained under different sample formation strategies

Model factors	Reweighted data			Thinned data		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
const	-4,752*** (0,000)	-4,146*** (0,000)	-5,487*** (0,000)	-4,673*** (0,000)	-4,319*** (0,000)	-5,572*** (0,000)
X_1	2,775*** (0,000)	2,919*** (0,000)	3,097*** (0,000)	2,584*** (0,000)	2,753*** (0,000)	2,890*** (0,000)
X_2	1,285** (0,028)	1,298** (0,025)		1,168 (0,130)	1,219 (0,104)	
X_3	1,242** (0,014)	1,167** (0,018)	3,255*** (0,001)	0,929 (0,145)	0,961 (0,116)	3,111** (0,015)
X_4	1,156** (0,047)		1,238** (0,041)	0,618 (0,370)		0,859 (0,246)
X_5	0,990** (0,041)			0,865 (0,150)		
$X_2 \cdot X_5$			3,427*** (0,000)			3,250*** (0,005)
$X_3 \cdot X_5$			-2,721*** (0,006)			-2,825** (0,032)
$X_4 \cdot X_5$		2,026*** (0,006)			1,309* (0,094)	
Log likelihood	-64,50	-64,07	-57,67	-42,29	-42,27	-38,05
LR statistic	86,68	87,55	100,34	41,71	41,74	50,18
p-value for the LR statistic	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Hosmer-Lemeshow statistic	5,52	6,89	6,08	2,69	3,88	2,87
p-value for the Hosmer-Lemeshow statistic	0,7009	0,2288	0,5303	0,9523	0,5665	0,8969

Source: calculated by the authors

CONCLUSIONS FROM THIS RESEARCH AND FURTHER PROSPECTS IN THIS DIRECTION

As a result of the conducted research, a comprehensive econometric approach to forecasting the investment attractiveness of IT projects under conditions of high stochasticity of the digital economy has been developed and empirically substantiated. The application of the logistic regression apparatus allowed transforming disparate performance indicators of 176 Ukrainian IT initiatives into a clearly structured model for management decision support.

Analysis of the constructed logit model parameters proved that the foundation of successful fundraising is the presence of early investor support, a clear commercial orientation toward profit generation, and an extensive digital presence of the company. At the same time, the main empirical achievement is the quantitative confirmation of the shift in venture capital priorities: investors give unconditional preference to reflexive-adaptive Agile management models. The existence of a powerful synergistic effect between high technological innovativeness (integration of AI/ML as the product core) and operational flexibility of the team (Time-to-Market speed of less than 6 months) has been proven. For IT projects with a standard technology stack, the primary orientation toward the corporate B2B segment remains a critically important compensator of investment risks.

The practical significance of the obtained models lies in their readiness for implementation in project management processes. IT project managers, product managers, and venture investors receive an effective analytical toolkit for auditing technological initiatives at early stages of the life cycle. This allows minimizing the risks of falling into the "valley of death", optimizing the allocation of financial resources, and making informed adjustments to the product commercialization strategy.

Future research prospects involve leveraging global Big Data to construct dynamic economic models based on recurrent neural networks (RNNs), which will enable the forecasting of temporal evolutionary trajectories of IT projects and facilitate the integration of these algorithms into automated systems to substantiate strategic managerial decisions.

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ЕКОНОМЕТРИЧНЕ МОДЕЛЮВАННЯ ІНВЕСТИЦІЙНОЇ ПРИВАБЛИВОСТІ ІТ-ПРОЄКТІВ НА ОСНОВІ ЛОГІСТИЧНОЇ РЕГРЕСІЇ

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Метою даного дослідження є розроблення економетричного інструментарію для визначення та кількісного оцінювання факторів, що впливають на ймовірність залучення зовнішнього фінансування ІТ-проєктами в умовах цифрової економіки.

Методологічна база ґрунтується на методах економетричного моделювання, зокрема бінарній логістичній регресії (логіт-моделі), а також системному аналізі, статистичних методах обробки даних та підходах до роботи з незбалансованими вибірками (перезважування та проріджування). Верифікацію моделей здійснено за критерієм Вальда, тестом відношення правдоподібності та тестом Хосмера–Лемешоу на якість підганяння.

На основі моделювання вибірки українських ІТ-проєктів було визначено ключові детермінанти успішного фандрейзингу. Встановлено вирішальний вплив наявності ранніх інвесторів, що суттєво підвищує ймовірність отримання фінансування. Підтверджено статистично значущий додатний вплив комерційної орієнтації проєкту та цифрової присутності. Крім того, обґрунтовано синергетичний ефект між технологічною інноваційністю, зокрема використанням штучного інтелекту, та операційною гнучкістю – що виявляється у скороченні часу виходу на ринок.

Запропонований підхід може бути застосований як інструмент підтримки прийняття рішень в управлінні ІТ-проєктами, зокрема для оцінювання інвестиційної привабливості, оптимізації стратегій розвитку та підвищення ефективності процесів комерціалізації інноваційних продуктів. Практичне значення розроблених моделей полягає в їхній здатності надати ІТ-менеджерам та венчурним інвесторам аналітичний інструментарій для аудиту ініціатив на ранніх етапах, тим самим мінімізуючи ризики «долини смерті» та оптимізуючи розподіл фінансових ресурсів. Практичне значення запропонованих моделей полягає в їхній спроможності надати ІТ-менеджерам та венчурним інвесторам аналітичний інструментарій для аудиту ініціатив на ранніх етапах, тим самим мінімізуючи ризики «долини смерті» та оптимізуючи розподіл фінансових ресурсів. Отримані результати сприяють зниженню ризиків на ранніх етапах життєвого циклу проєкту та підвищують надійність управлінських рішень. Майбутні напрямки досліджень передбачають використання рекурентних нейронних мереж для прогнозування довгострокових тенденцій розвитку ІТ-продуктів на глобальному цифровому ринку.

Ключові слова: ІТ-проєкт, ІТ-продукт, цифрова економіка, управління проєктами, логістична регресія, оптимізація, моделювання, інвестиційна привабливість.