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ECONOMIC EFFICIENCY OF A DIGITAL DEVELOPMENT STRATEGY UNDER WARTIME CRISIS

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The article presents a comprehensive assessment of the economic efficiency of implementing an enterprise digital development strategy in the practice of an information technology company operating under the wartime crisis caused by Russia's full-scale invasion of Ukraine. The purpose is to evaluate the economic effect of the strategy through return on investment, payback period, and net present value, to deploy a scenario assessment of the expected effect under different developments of the crisis, to apply machine-learning forecasting of financial and operational indicators, and to summarize the dynamics of key performance indicators before and after implementation. The methodology integrates financial analysis, probabilistic scenario modeling, and an ensemble of machine-learning models for revenue forecasting; the monetized reduction of risk is reported separately from the cash flow to avoid double counting, and the riskiness of the environment is captured through scenario probabilities and the discount rate. Three scenarios were defined, namely pessimistic, base, and adaptive-recovery, with assigned probabilities. The expected economic effect amounted to 287.5 thousand euro against 96 thousand euro of investment, which corresponds to an expected return on investment of 299.5 percent, a payback period of about three months, and a net present value of 246.4 thousand euro at a discount rate of twelve percent, remaining positive under sensitivity testing at eighteen and twenty-five percent. Labor productivity rose by 28.1 percent and the operating cost ratio fell from 0.74 to 0.66, while the forecasting ensemble reached an average error of about eleven percent. Unlike a deterministic appraisal, the proposed framework separates realized cash effects from risk exposure and demonstrates how scenario probabilities, discounting, and forecast accuracy can be jointly used to support investment decisions under wartime uncertainty. The practical value is a reproducible, scenario-aware toolkit for justifying digital investment under deep uncertainty. The approach can be repeated by using the same input groups, scenario probabilities, forecasting metrics, and financial indicators, which makes the assessment transparent for managers, investors, and reviewers. It also clarifies how crisis-driven benefits, such as avoided downtime and preserved revenue, can be converted into comparable investment indicators without overstating the cash effect.

Keywords: economic efficiency, digital development strategy, return on investment, net present value, scenario analysis, machine-learning forecasting, labor productivity, wartime crisis.

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INTRODUCTION

Russia's full-scale invasion of Ukraine turned the digital development of enterprises into a condition of survival and a measurable economic factor. Evidence from Ukrainian firms in a war economy shows that resilience follows organizational pathways rather than a single recovery rule [1], while large-sample studies confirm that digital transformation raises firm resilience and financial performance [2, 3]. For an information technology company, whose principal resource is human capital and whose delivery depends on continuous access to data and services, a digital strategy is at the same time a major investment that must be economically justified. The problem addressed here is that conventional methods of evaluating information technology investment, based on deterministic return on investment and net present value, do not capture the multiple ways a crisis may unfold and therefore understate the value of digital initiatives that reduce crisis losses. The scientific and practical significance of the problem lies in the need for a scenario-aware, forecasting-supported assessment that demonstrates, in monetary terms, the economic efficiency of a digital development strategy implemented under wartime conditions.

ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS

The economic effects of digital transformation are well documented. Cardoso et al. [4] traced the move from crisis response to digital business model renewal; Őri et al. [5] showed how firms activate resilience to drive digitalization in a crisis; and Sagala and Őri [6] linked digital transformation strategy to resilience and antifragility. From a capabilities angle, Liu et al. [7] demonstrated that digital orientation strengthens resilience through sensing and reconfiguration. On the analytical side, Smyth et al. [8] reviewed artificial intelligence and prescriptive analytics as drivers of resilience, which underpins the use of machine-learning forecasting in financial planning. The relevance of machine learning and data science for modern business efficiency, forecasting, and decision-making was also emphasized by Reznikov and Turlakova [9]. In parallel, globalization and international integration have been examined as a crisis management strategy for mitigating organizational risks [10], which supports the interpretation of export orientation and access to external markets as part of the economic environment in which digital investment is evaluated. The evaluation of digital initiatives as investments draws on the project portfolio literature: Aghajani et al. [11] show that prioritization and value assessment dominate the field, and Han and Zhao [12] formalize portfolio value with explicit project synergy. Readiness research, in turn, links the capacity to absorb technology with realized value [13]. Two aspects remain insufficiently addressed. First, the evaluation of digital investment rarely combines probabilistic crisis scenarios with machine-learning forecasting in a single framework. Second, few studies present firm-level economic results of a digital strategy implemented under an acute crisis such as full-scale war. This article addresses both for a Ukrainian technology company.

THE AIM AND OBJECTIVES OF THE STUDY

The aim of the study is to assess the economic efficiency of implementing an enterprise digital development strategy in the practice of an information technology company under wartime crisis. The objectives are to evaluate the economic effect through return on investment, payback period, and net present value; to deploy a scenario assessment of the expected effect under different developments of the crisis; to apply machine-learning forecasting of financial and operational indicators; and to summarize the dynamics of the key performance indicators of the enterprise before and after implementation.

PRESENTATION OF THE MAIN MATERIAL OF THE STUDY

The economic effect of the digital strategy is defined as the sum of additional or retained revenue, operating cost savings, and avoided losses, net of investment, with the monetized reduction of risk reported separately:

$$EE = \Delta R + \Delta C + \Delta L - I \tag{1}$$

Return on investment, payback period, and net present value over a one-year horizon are determined as follows:

$$ROI = EE / I \times 100\ \% \tag{2}$$

$$PBP = I / ((\Delta R + \Delta C + \Delta L) / 12) \tag{3}$$

$$NPV = CF_1 / (1 + r) - I_0,\ CF_1 = \Delta R + \Delta C + \Delta L \tag{4}$$

where *EE* is the economic effect; ΔR, ΔC, and ΔL are additional revenue, cost savings, and avoided losses; *I* is investment; CF_1 is the annual gross cash inflow; and *r* is the discount rate, set at 12 percent. To avoid double counting, the monetized reduction of risk is not included in the cash flow; the riskiness of the environment is captured through scenario probabilities and the discount rate.

To reflect the uncertainty of the war, three scenarios were defined: a base scenario assuming stabilization at a controlled level of risk; a pessimistic scenario assuming intensified energy, staffing, and security constraints; and an adaptive-recovery scenario assuming gradual growth of demand for technology services and deeper integration with European Union markets. The expected economic effect is the probability-weighted sum of the scenario effects:

$$EEE = \sum p\_s \cdot EE\_s \tag{5}$$

where *EEE* is the expected economic effect, p_s is the probability of scenario *s*, and EE_s is the economic effect under that scenario. The scenario assessment is reported in Table 1 and visualized in Figure 1.

Table 1.

Scenario assessment of the economic effect of the digital development strategy

Scenario	Probability	Economic effect, thousand EUR	Weighted contribution, thousand EUR
Pessimistic	0.25	176	44.0
Base	0.50	295	147.5
Adaptive-recovery	0.25	384	96.0
Expected effect (EEE)	1.00	287.5	287.5

Source: developed by the author.

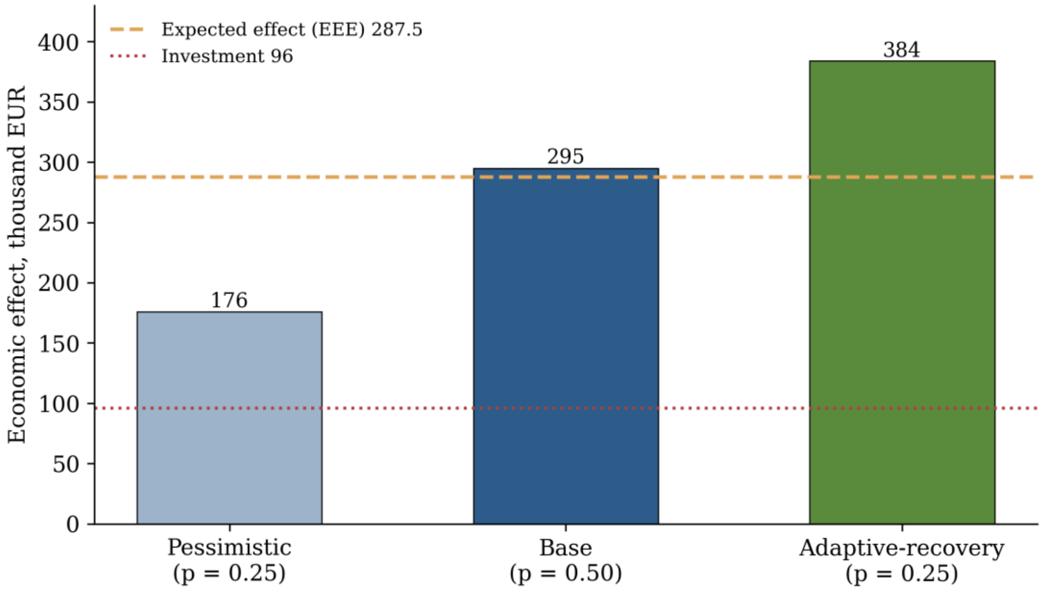

Fig. 1. Scenario economic effects and the expected effect of the digital strategy

The expected economic effect amounted to 287.5 thousand euro. For the studied company three values are distinguished by contour and method: 186 thousand euro is the effect of business continuity projects alone; 295 thousand euro is the deterministic sum of effects across seven directions of digital transformation; and 287.5 thousand euro is the expected effect weighted by the probabilities of the three scenarios. The lower value of the expected effect reflects the pessimistic scenario taken with probability 0.25. Against total investment of 96 thousand euro, the expected return on investment was 299.5 percent and the payback period was about three months, computed from the annual gross inflow, which equals the expected effect plus the initial investment. At a discount rate of 12 percent the net present value over the one-year horizon was 246.4 thousand euro. Because the wartime environment carries elevated risk, the net present value was tested for sensitivity to the discount rate: it remained at 229.0 thousand euro at 18 percent and 210.8 thousand euro at 25 percent, as shown in Figure 2, which confirms the economic soundness of the strategy. The discount rate is jurisdiction-specific; for the Ukrainian company it was formed as a risk-free yield with a risk premium, moderated by the export orientation and foreign currency revenue of the company.

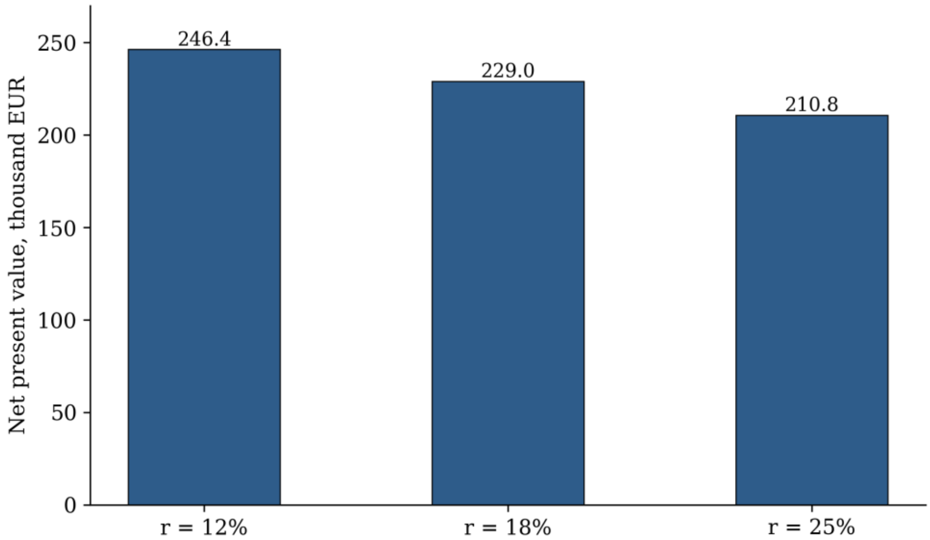

Fig. 2. Sensitivity of the net present value to the discount rate

To deepen the assessment, machine-learning forecasting of financial and operational indicators was applied. The forecast revenue is treated as a function of internal and external factors:

$$R(t+1) = f\_AI(R(t), Pipeline, Util, HRS, FX, GDP, WarRisk, Demand) \quad (6)$$

where R(t+1) is the forecast revenue, fAI is the ensemble forecasting function, and the arguments are current revenue, the sales pipeline, team utilization, workforce stability, the currency factor, macroeconomic dynamics, the level of war risk, and expected demand for technology services. The function was implemented through an ensemble of gradient boosting, a long short-term memory network, and a transformer model, trained on company data for 2020 to 2024 and validated out of sample on 2025 data. The comparison of models is reported in Table 2.

Table 2.

Out-of-sample accuracy of the revenue forecasting models (2025)

Model	MAPE, %	RMSE (relative)	R-squared
Gradient boosting (XGBoost)	14.2	0.121	0.86
LSTM network	13.1	0.112	0.88
Transformer	12.4	0.104	0.89
Ensemble	11.3	0.095	0.91

Source: developed by the author.

The managerial value of forecasting lies not in accuracy as such but in better decisions. The monetized value of the forecast is estimated as:

$$V = \alpha \cdot (MAPE\_base - MAPE\_AI) \cdot R \tag{7}$$

where $MAPE_{base}$ is the error of a naive forecast, $MAPE_{AI}$ is the error of the ensemble, R is annual revenue, and a is the sensitivity of staffing and resource costs to planning error. With a naive error of about 21 percent, an ensemble error of about 11.3 percent, and a sensitivity of about 0.15, the forecast saved roughly 14.5 percent of resource-planning costs, which turns the forecasting result from a technical into an economic one.

The digital strategy also improved the operational performance of the enterprise. Labor productivity and the operating cost ratio are defined as:

$$LP = R / N \tag{8}$$

$$OCR = OC / R \tag{9}$$

where LP is labor productivity, R is revenue, N is the average number of staff, OCR is the operating cost ratio, and OC is operating cost. Labor productivity rose from 48.0 to 61.5 thousand euro per employee, an increase of 28.1 percent, while the operating cost ratio fell from 0.74 to 0.66. The dynamics of the key indicators are summarized in Table 3.

Table 3.

Dynamics of the key performance indicators of the company before and after implementation

Indicator	Before	After	Change
Organizational readiness (OGR)	0.48	0.82	+70.8%
Workforce stability (HRS)	0.57	0.84	+47.4%
Digital readiness (DGI)	0.49	0.82	+67.3%
Labor productivity, thousand EUR per employee	48.0	61.5	+28.1%
Operating cost ratio (OCR)	0.74	0.66	-10.8%
Recovery time objective, h	48	6	-87.5%
Recovery point objective, h	24	2	-91.7%

Source: developed by the author.

Compared with other Ukrainian technology companies that operated during the war without an integrated digital strategy, whose labor productivity moved between minus five and plus ten percent and whose operating cost ratio rose under inflationary and security pressure, the results of the studied company show a clear advantage of the systematic approach. The strategy also supported the national economy: the export revenue of the company grew by about 32 percent against the pre-war level, with most of it converted into foreign currency inflows to Ukraine, which contributes to currency stability in a crisis period.

CONCLUSIONS

The study assessed the economic efficiency of implementing a digital development strategy in an information technology company under wartime crisis and confirmed its high efficiency. The expected economic effect, weighted across three crisis scenarios, amounted to 287.5 thousand euro against 96 thousand euro of investment, which corresponds to an expected return on investment of 299.5 percent, a payback period of about three months, and a net present value of 246.4 thousand euro that remains positive under sensitivity testing at higher discount rates. Machine-learning forecasting, built as an ensemble of gradient boosting, a long short-term memory network, and a transformer, reached an average error of about 11.3 percent and delivered measurable managerial value by reducing resource-planning losses. The strategy raised labor productivity by 28.1 percent and lowered the operating cost ratio from 0.74 to 0.66, while sharply improving the parameters of business continuity. The scientific contribution is the integration of probabilistic crisis scenarios and machine-learning forecasting into a single framework for evaluating digital investment, and the practical contribution is a reproducible toolkit that managers can apply to justify digital investment under deep uncertainty. Further research will extend the approach to other sectors and couple the scenario assessment with a multi-year evaluation horizon.

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Conflict of Interest
The author declares no conflict of interest.

REFERENCES:

1. de Waal, G. A., Kenworthy, A. L., Opatska, S., Trevoho, O., Boychuk, Y., & Kozlova, V. (2025). Exposing pathways to organisational resilience: Revenue recovery patterns among Ukrainian firms in a war economy. Journal of Contingencies and Crisis Management, 33(1), e70058. https://doi.org/10.1111/1468-5973.70058
2. Xu, Y., Xu, L., Shen, Y., & Fan, Z. (2024). Exploring the effect of digital transformation on firm resilience: Evidence from China. Journal of Asian Economics, 95, 101812. https://doi.org/10.1016/j.asieco.2024.101812
3. Zheng, X., & Bu, Q. (2024). Enterprise ESG performance, digital transformation, and firm performance: Evidence from China. SAGE Open, 14(4), 1–18. https://doi.org/10.1177/21582440241291680
4. Cardoso, A., Figueiredo, J., Oliveira, I., & Pocinho, M. (2025). From crisis to opportunity: Digital transformation, digital business models, and organizational resilience in the post-pandemic era. Administrative Sciences, 15(6), 193. https://doi.org/10.3390/admsci15060193
5. Őri, D., Szabó, I., Kő, A., & Kovács, T. (2024). Digitalizing in crisis: The role of organizational resilience in SMEs' digitalization. Journal of Enterprise Information Management, 37(4), 1185–1205. https://doi.org/10.1108/JEIM-03-2023-0141
6. Sagala, G. H., & Őri, D. (2024). Exploring digital transformation strategy to achieve SMEs resilience and antifragility: A systematic literature review. Journal of Small Business & Entrepreneurship, 36(4), 495–524. https://doi.org/10.1080/08276331.2024.2392080
7. Liu, Y., Guo, M., Han, Z., Gavurova, B., Bresciani, S., & Wang, T. (2024). Effects of digital orientation on organizational resilience: A dynamic capabilities perspective. Journal of Manufacturing Technology Management, 35(2). https://doi.org/10.1108/JMTM-06-2023-0224
8. Smyth, C., Dennehy, D., Fosso Wamba, S., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: A systematic literature review and research agenda. International Journal of Production Research, 62(23), 8537–8561. https://doi.org/10.1080/00207543.2024.2341415
9. Reznikov, R., & Turlakova, S. (2024). Importance of machine learning and data science in modern business. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4851005
10. Reznikov, R. (2024). Globalization as a crisis management strategy: Mitigating organizational risks through international integration. International Economic Policy, 1(40), 175–189. https://doi.org/10.33111/iep.eng.2024.40.07
11. Aghajani, M., Ruge, G., & Jugdev, K. (2023). An integrative review of project portfolio management literature: Thematic findings on sustainability mindset, assessment, and integration. Project Management Journal, 54(6), 629–650. https://doi.org/10.1177/87569728231172668
12. Han, R., & Zhao, Z. (2024). Research on project portfolio selection problem considering project synergy under multiple mental accounts. Soft Computing, 28, 12655–12670. https://doi.org/10.1007/s00500-024-10321-0
13. Michelotto, F., & Joia, L. A. (2024). Organizational digital transformation readiness: An exploratory investigation. Journal of Theoretical and Applied Electronic Commerce Research, 19(4), 3283–3304. https://doi.org/10.3390/jtaer19040159

ЕКОНОМІЧНА ЕФЕКТИВНІСТЬ ЦИФРОВОЇ СТРАТЕГІЇ РОЗВИТКУ В УМОВАХ ВОЄННОЇ КРИЗИ

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У статті представлено комплексне оцінювання економічної ефективності впровадження цифрової стратегії розвитку підприємства в практику функціонування компанії сфери інформаційних технологій в умовах воєнної кризи, спричиненої повномасштабним вторгненням Росії в Україну. Мета полягає в оцінюванні економічного ефекту стратегії через рентабельність інвестицій, строк окупності та чистий приведений ефект, у розгортанні сценарної оцінки очікуваного ефекту за різних варіантів розвитку кризи, у застосуванні прогнозування фінансових та операційних показників на основі машинного навчання, а також в узагальненні динаміки ключових показників діяльності до та після впровадження. Методологія поєднує фінансовий аналіз, імовірнісне сценарне моделювання та ансамбль моделей машинного навчання для прогнозування доходу; монетизоване зниження ризику подається окремо від грошового потоку задля уникнення подвійного врахування, а ризиковість середовища враховується через імовірності сценаріїв і ставку дисконтування. Сформовано три сценарії, а саме песимістичний, базовий та адаптивно-відновлювальний, з відповідними ймовірностями. Очікуваний економічний ефект становив 287,5 тисячі євро за інвестицій 96 тисяч євро, що відповідає очікуваній рентабельності інвестицій 299,5 відсотка, строку окупності близько трьох місяців і чистому приведеному ефекту 246,4 тисячі євро за ставки дисконтування дванадцять відсотків, який залишається додатним за перевірки чутливості на рівні вісімнадцять і двадцять *п'ять відсотків. Продуктивність праці зросла на 28,1 відсотка, а частка операційних витрат у доході знизилася з 0,74 до 0,66, тоді як прогнозний ансамбль досяг середньої похибки близько одинадцяти відсотків. На відміну від детермінованої оцінки, запропонований підхід відокремлює реалізовані грошові ефекти від ризикової експозиції та показує, як імовірності сценаріїв, дисконтування і точність прогнозування можуть спільно підтримувати інвестиційні рішення в умовах війни. Практична цінність полягає у відтворюваному, чутливому до сценаріїв інструментарії обґрунтування цифрових інвестицій в умовах глибокої невизначеності. Підхід може бути відтворений із використанням тих самих груп вхідних даних, імовірностей сценаріїв, прогнозних метрик і фінансових показників, що робить оцінювання прозорим для менеджерів, інвесторів і рецензентів. Він також уточнює, як кризові вигоди, зокрема уникнення простоїв і збереження доходу, можуть бути перетворені на зіставні інвестиційні показники без завищення грошового ефекту.*

Ключові слова: економічна ефективність, цифрова стратегія розвитку, рентабельність інвестицій, чистий приведений ефект, сценарний аналіз, прогнозування на основі машинного навчання, продуктивність праці, воєнна криза.