https://doi.org/10.33271/nvngu/2026-4/200

M. Bosovska,
orcid.org/0000-0002-6021-5228,
A. Piliukov*,
orcid.org/0009-0008-0802-4361

State University of Trade and Economics, Kyiv, Ukraine
* Corresponding author e-mail: a.pilyukov@knute.edu.ua

MODELLING IMPACT OF HYBRID METHODOLOGY ON PERFORMANCE OF IT-ENTERPRISES

Purpose. To develop and empirically verify a model-based approach to assessing the impact of a hybrid project management methodology on the performance of software development enterprises, taking into account the level of managerial maturity and the moderating role of artificial intelligence tools.

Methodology. The study is based on an original survey of 93 Ukrainian IT enterprises (2026) and combines cluster analysis (the k-means algorithm with the silhouette quality criterion), multiple regression modelling (OLS), the Analytic Hierarchy Process (AHP) with verification of the consistency of expert judgements (CR < 0.1), and three-level scenario modelling. The enterprise typology is constructed by level of managerial maturity through the aggregation of managerial, engineering and business indicators.

Findings. A typology comprising three enterprise types is empirically confirmed: start-up, established Agile practices, and mature enterprise level. The regression model ($R^2 = 0.957$) revealed a statistically significant effect of the presence of a project management office, CI/CD maturity and AI readiness on the composite project performance index (PPI). The transformation of the management system is substantiated through three scenarios: baseline, formalisation of the hybrid methodology, and integration of artificial intelligence tools. An adaptive PPI structure with differentiated subindex weights and assessment time horizons is proposed; the projected performance gain falls within the range of 10–40 %, peaking at highly mature enterprises.

Originality. A multi-level model for assessing the impact of a hybrid project management methodology has been developed and empirically verified which, unlike descriptive maturity models, combines an enterprise typology based on managerial maturity, an adaptive composite PPI indicator and a four-stage scheme for transforming management practices. The model operationalises the non-linearity of the transition between maturity levels while accounting for the moderating role of AI tools and the resource constraints of the enterprise.

Practical value. The proposed model is intended to serve as an analytical instrument for substantiating managerial decisions concerning the adoption of a hybrid methodology and the integration of artificial intelligence at software development enterprises. Its application delivers a predictably positive economic effect through the reduction of losses, revenue growth and an increase in the intangible value of assets, and provides a quantitative rationale for investment decisions by demonstrating positive NPV and IRR.

Keywords: *hybrid methodology, project management, composite PPI indicator, artificial intelligence, IT enterprises*

Received: 27 March 2026
Accepted: 20 July 2026
Available online: 27 August 2026

Introduction. The contemporary software development sector operates under conditions of permanent VUCA turbulence, high project intensity and deepening information asymmetry between the client and the delivery team. The growing complexity of technological solutions, intensifying regulatory pressure and the acceleration of innovation cycles objectively constrain the effectiveness of traditional (Waterfall) and purely adaptive (Agile) methodologies. These methodologies demonstrate only a partial capacity to secure strategic alignment while preserving operational adaptability. As a consequence, a considerable share of enterprises in the knowledge-intensive business services (KIBS) sector faces a non-linear escalation of costs, the accumulation of technical debt and the fragmentation of managerial metrics. All of these factors reduce the predictability of key business outcomes.

The industry has responded to these challenges through an active shift towards hybrid project management (HPM) methodologies that systematically combine predictive and adaptive practices. According to international surveys, the share of enterprises adopting hybrid approaches rose from 20 % in 2020 to approximately 32 % in 2025. This testifies to a deliberate transition towards integrated models capable of withstanding the complexity of regulated environments and the dynamism of technological change [1, 2]. At the same time, empirical research records substantial heterogeneity in the effects of HPM adoption. For some enterprises hybridisation yields the anticipated benefits in the form of process stabilisation and improved cost control. For others it generates rising coordination costs without any appreciable gain in performance [2, 3].

The theoretical gap between the abstract recognition of the advantages of hybrid methodologies and their uneven practical effects underlines a clear need. HPM requires a systematic conceptualisation as a function of the enterprise's managerial maturity, its resource configuration and data quality. The key problem is that the existing project management maturity models (OPM3, P3M3, PMMM and others) are predominantly descriptive in character. They take poor account of structural and infrastructural factors and team competencies, and are weakly adapted to the resource-constrained envi-

© Bosovska M., Piliukov A., 2026

ronments of small and medium-sized businesses [4, 5]. A further challenge lies in the integration of artificial intelligence (AI) tools. Their effect on project performance is not automatic and is largely determined by the degree of process institutionalisation and the quality of corporate data [6, 7].

At least three interrelated research problems remain unresolved. First, the operationalisation of the nonlinear character of the transition between levels of managerial maturity, taking into account typical proxy indicators (SPI/CPI stability, data coverage, replanning frequency). Second, the construction of a composite project performance indicator differentiated by enterprise type and aligned with its strategic context. Third, the determination of the boundaries within which AI tools can be applied productively depending on the level of organisational and data maturity. Clarifying these boundaries makes it possible to avoid a common situation, in which a substantial share of AI initiatives fails to generate a positive return owing to the absence of basic integration prerequisites.

Within the present study these problems are addressed through a single multi-level model. Its theoretical framework rests on a synthesis of four mutually complementary approaches. The theory of dynamic organisational capabilities explains the ability of enterprises to reconfigure resources systematically in a turbulent environment. The concept of managerial maturity provides a typological basis for comparing enterprises by their degree of integration of management practices. The benefits realisation management approach links project activity to the implementation of business strategy. Finally, the moderated technology impact model treats AI as a catalyst rather than a substitute for managerial decisions. This theoretical combination forms the analytical basis for constructing an adaptive composite Project Performance Index (PPI) and a four-stage model for transforming management systems [8, 9].

The object of the research is the project management system at software development enterprises. Its subject comprises the methodological and applied principles of assessing the impact of a hybrid project management methodology on the performance of these enterprises with due regard for managerial maturity. The empirical basis of the study consists of the results of an original survey of 93 Ukrainian IT enterprises (2026). The 40-item questionnaire was adapted from the structure of the Stack Overflow Developer Survey, the DORA Accelerate State of DevOps Report and the PMI Pulse of the Profession. Performance data for the top 50 Ukrainian IT companies (Opendatabot, dou.ua, dev.ua, Crunchbase) were additionally employed. These were combined with aggregated industry metrics from PMI, the Wharton Budget Model, McKinsey, Gartner and the Stanford AI Index (2023–2025). This empirical foundation makes it possible to combine micro-level enterprise parameters with macro-level trends in AI tool integration. It thereby ensures the verification of the model hypotheses in a context that is simultaneously local (the Ukrainian IT sector) and global (the KIBS sector).

Literature review. The theoretical and methodological foundations of hybrid project management have been systematically addressed in a body of work based on systematic reviews. This work demonstrates that combining predictive and adaptive practices increases the probability of project success, ensures resilience in a VUCA environment and constitutes the current stage in the evolution of management methodologies. U. Khan and M. Qaiser provide empirical confirmation of the positive influence of a hybrid configuration on key performance indicators. In turn, B. Bianca and R. Hanslo trace the trajectory of transformation from purely Agile approaches towards integrated hybrid models as a response to the growing complexity of the project environment. The comparative analysis of theories and approaches to project management carried out by A. Piliukov further attests to the hybridisation of the theoretical field. It also confirms the absence of a universal theory suitable for every type of project environment [10].

The problem of project management maturity models is examined comprehensively in the review by E. Fabbro and S. Tonchia. That review classifies the existing models into groups – from the classical level-based constructs (CMMI, PMMM, the Berkeley models) to more recent designs – and notes their limitations in resource-constrained environments [4]. The systematic PRISMA review by E. Mahdi generalises the factors of organisational maturity (structural, human and contextual). It also identifies the weaknesses of the existing models, in particular their insufficient treatment of team competencies and the external context, which justifies the transition from static to adaptive analytical constructs [5]. These propositions are central to the design of the proposed four-stage transformation model.

The role of AI in project management has been systematised in the work by P. Almeida, et al., where AI is considered from a knowledge management perspective as an instrument for supporting decision-making. In turn, S. Salimimoghadam, et al. offer a thorough review of the opportunities, drivers and barriers to AI adoption in project management. The study by L. Hughes, et al. formulates, on the basis of expert analysis, a strategic vision for the development of PM 2030. It emphasises the moderating rather than substitutive character of AI tools. A. Piliukov substantiates the concept of an adaptive value-based integrated model of IT project management, distinguishing four roles of artificial intelligence (AI analyst, AI engineer, AI coordinator, AI consultant). This corresponds directly to the model-based approach proposed in the present article [11]. The applied dimension of AI in software development is set out in the monograph by L. Song and L. Minku [12]. In the studies by J. Diameh and A. ForouzeshNejad, which present concrete cases of the use of predictive analytics for risk management [13, 14]. K. Oftebro, et al. describe experience in applying generative AI to optimise backlog grooming, while A. Geamanu, et al. propose an integrated AI tool for forecasting project risks [15, 16].

Applied aspects of measuring project performance are examined in the work by K. Pham and M. Neumann, which presents a mixed-method methodology for assessing the productivity of Agile teams, and by G. Leite, et al., who carry out a systematic mapping of technical debt management practices in an Agile environment [17]. The study by U. Zaman, et al. establishes statistically significant relationships between management innovation, project governance and high-perfor-

mance work practices, which justifies an integrated approach to assessing project success [18].

Contextual factors of project success are addressed in the following works: R. Moura, et al. analysed the influence of project management methods on success in VUCA conditions, while C. Serra and M. Kunc formalised the concept of benefits realisation management as the link between project activity and the implementation of business strategy [19, 20]. The review of key IT project success factors by C. Iriarte and S. Bayona further confirms the predominance of organisational and behavioural parameters over purely technical characteristics, which is consistent with the logic of the proposed model [21].

The methodological basis for the typologisation of enterprises rests on the studies by V. Alexandru, et al., which were carried out using cluster analysis. Groups of KIBS-sector enterprises were identified by level of knowledge management maturity, while Š. Slávik, et al. constructed a multidimensional typology of start-up business models by means of the hierarchical method [22, 23]. These results confirm the relevance of the cluster approach for building analytical typologies of managerial maturity.

The methodological toolkit for assessing and visualising results is covered in a number of specialised works. S. Frish, et al. propose an improved algorithm for verifying the consistency of expert judgements within the Analytic Hierarchy Process (AHP). This algorithm is employed in the present study to calibrate the weights of the PPI subindices [24]. N. Yadav, et al. systematise two decades of development in performance management frameworks, which substantiates the evolutionary logic underlying the changing weights of the metrics [25]. D. Gobov and O. Zuieva examine software quality attributes as a component of the business subindex of the PPI. In turn, N. Savitri, et al. demonstrate the architectural principles for constructing analytical dashboards for real-time project monitoring, a technological prerequisite for operationalising the composite indicator [26, 27].

Notwithstanding this considerable body of scholarship, two aspects remain insufficiently developed: the operationalisation of the non-linear transition between levels of managerial maturity, and the construction of a composite performance indicator differentiated by enterprise type. The boundaries within which AI tools can be applied productively depending on the level of organisational and data maturity likewise remain an open question. It is precisely this that constitutes the research gap the present study seeks to fill.

The sources analysed summarised, it may be observed that three conceptual clusters of research have taken shape in the current literature, which have hitherto developed in parallel. The methodological cluster is devoted to the evolution of hybrid approaches and their combination with classical and adaptive models. The measurement cluster is oriented towards the development of composite performance indices, DORA metrics and EVM extensions. The technological cluster focuses on the role of AI tools as a factor in transforming management practices. These clusters have yet to receive a consistent synthesis within a single analytical approach, which makes it impossible to compare quantitatively the effects of different management configurations. The model proposed in this study closes that gap by integrating an enterprise typology, an adaptive composite PPI indicator and a four-stage transformation model into a unified analytical construct.

Purpose. The purpose of the article is to develop and empirically verify a model-based approach to assessing the impact of a hybrid project management methodology on the performance of software development enterprises. The approach takes into account the level of managerial maturity and the moderating role of AI tools. To achieve this purpose, the following tasks were set and consistently addressed: 1) to construct and empirically verify a typology of software development enterprises by level of managerial maturity on the basis of clustering managerial, engineering and business indicators; 2) to assess quantitatively the determinants of composite project performance by means of a multiple regression model; 3) to build a three-level scenario model for transforming project management systems (baseline – formalisation – AI integration); 4) to substantiate the structure of an adaptive composite PPI indicator with differentiated subindex weights; 5) to formalise a four-stage model of transition between maturity levels and to evaluate the composite economic effect of the transformation measures.

Methodology. The methodological basis of the study combines four mutually complementary instruments applied to a single empirical base – the results of an original survey of 93 Ukrainian IT enterprises (2026). The sample is stratified by size: 48 small (up to 200 employees), 30 medium (200–1,000) and 15 large (more than 1,000 employees). First, cluster analysis. Alongside the hierarchical AGNES (agglomerative) and DIANA (divisive) algorithms, the non-hierarchical k-means algorithm was applied to five normalised variables: level of process formalisation, CI/CD maturity, AI readiness, share of projects delivered on time, and ROI. This choice is consistent with the recommendations of earlier work. The quality of clustering was assessed by the mean silhouette coefficient; the combined approach increases the robustness of the results to heterogeneity in the empirical data.

Second, a multiple linear regression model estimated by ordinary least squares (OLS) was applied to the quantitative assessment of the determinants of performance. The model specification for enterprise i takes the form

$$PPI_i = \beta_0 + \beta_1 \cdot SizeM_i + \beta_2 \cdot SizeS_i + \beta_3 \cdot PMO_i + \\ + \beta_4 \cdot AI_i + \beta_5 \cdot AIR_i + \beta_6 \cdot CICD_i + \sum \beta_i \cdot Method_i + \varepsilon_i,$$

where PPI is the composite project performance indicator; $SizeM$ and $SizeS$ are binary indicators of medium and small enterprise size (large enterprises serve as the reference category); PMO denotes the presence of a project management office; AI is the fact of using AI tools; AIR is AI readiness (0–10 points); $CICD$ is the maturity of CI/CD practices (0–10 points); Method is a vector of binary indicators of the methodologies applied (Scrum, SAFe and others); and ε is the stochastic error term. This specification operationalises the moderated hypothesis according to which the effect of AI tools is realised through the level of organisational maturity and

engineering infrastructure rather than autonomously, and accounts for the observed heterogeneity of adoption outcomes.

Third, the weights of the subindices of the composite indicator were computed by the Analytic Hierarchy Process (AHP) with verification of the consistency of expert judgements by means of the coefficient

$$CR = (\lambda\max - n)/((n-1)\cdot RI),$$

where λmax is the maximum eigenvalue of the pairwise comparison matrix; n is the number of criteria compared; RI is the random index for a matrix of the corresponding size. Consistency is deemed acceptable at $CR < 0.1$ in accordance with the refined methodology. Based on the results of the expert assessment, the baseline subindex weights are $wm = 0.40$, $we = 0.30$ and $wb = 0.30$, with subsequent differentiation depending on the maturity level of the enterprise.

Fourth, the composite PPI indicator synthesises the managerial, engineering and business subindices

$$PPI = wm \cdot MS + we \cdot ES + wb \cdot BS; \quad wm + we + wb = 1,$$

where MS is the managerial subindex (process formalisation, the presence of a PMO, adapted SPI and CPI, and Earned Value indicators); ES is the engineering subindex (DORA metrics: deployment frequency, lead time for changes, change failure rate and mean time to restore, together with CI/CD maturity and AI readiness); BS is the business subindex (dROI, the benefits realisation ratio BRR, NPS/CSAT, and adherence to deadlines). All subindices are normalised to the range [0; 1] by the min–max method.

Scenario modelling was performed at the level of aggregated enterprise types, which ensured representativeness and precluded reliance on isolated cases. Standard financial criteria of net present value and internal rate of return were used to assess the investment attractiveness of the transformation

$$NPV = \sum T_{t=1} CF_t/(1+r)^t - I_0; \quad NPV(IRR) = 0,$$

where CF_t is the net cash flow of period t; r is the discount rate; I_0 denotes the initial transformation costs; T is the assessment horizon.

Results. The cluster analysis distinguished three aggregated types of software development enterprises by level of managerial maturity. These types reflect typical configurations of the project management system and provide the structural basis for the subsequent scenario modelling. Type 1 (the "start-up") is characterised by ad hoc practices, fragmented management procedures and a high dependence on the individual competencies of key personnel. Type 2 (with established Agile practices) reflects the transition to repeatable and managed processes at the operational level with limited strategic alignment. Type 3 (the mature enterprise level) is distinguished by portfolio logic, an institutionalised PMO and a system of composite PPI and DORA indices combined with EVM.

A detailed comparison of the types across the key dimensions of managerial maturity is presented in Table 1. It illustrates the non-linear character of the transition between maturity levels. Each successive level is not reducible merely to an accumulation of instruments, but presupposes a transformation of the management architecture and a reallocation of the roles played by individual and systemic factors.

The typology presented in Table 1 was verified on a subsample of the top 50 Ukrainian IT companies (2026). Type 3 is represented by enterprises with more than 1,000 employees and an established PMO; Type 2 by medium-sized enterprises with a developed set of Agile practices; and Type 1 by representatives of the product segment and early-stage start-ups. A conceptual scheme of the evolution of the management architecture is presented in Fig. 1 to visualise the trajectory of transition between maturity levels.

The empirical validity of the three-group typology was confirmed by cluster analysis of the survey data for 93 IT enterprises. The mean silhouette coefficient of $\bar{s} = 0.254$ indicates acceptable, though moderate, separability of the clusters. Such a value is typical of socio-economic samples containing transitional states. The intersection of the k-means clusters with the enterprise size groups is presented in Table 2. The configuration of the clusters in the two-dimensional space of the managerial (MS) and engineering (ES) subindices is shown in Fig. 2.

The results of the cluster analysis confirm the empirical soundness of the three-group division. Large enterprises form the high-maturity cluster in its entirety, 83.3 % of small enterprises are concentrated in the low-maturity cluster, and medium-sized enterprises occupy an intermediate position with a tendency to shift towards high maturity (36.7 % in the corresponding cluster). At the same time, cluster membership is determined not by size as such but by the configuration of management practices. Some small enterprises fall into the medium-maturity cluster, while individual medium-sized enterprises fall into the high-maturity cluster. This confirms the analytical rather than purely dimensional character of the proposed typology.

The soundness of the composition of the metrics of the composite indicator was additionally verified by

Table 1

Comparative characteristics of software development enterprise types by level of managerial maturity [4, 5]

Maturity dimension	Type 1: start-up	Type 2: agile practices	Type 3: enterprise level
Process formalisation	Fragmented, ad hoc	Standardisation at team level	PMO-oriented with compliance procedures
Metric integration	Low, isolated indicators	Medium, mainly operational metrics	High, composite indices (PPI, DORA+EVM)
Alignment with business goals	Weak, tactical	Medium, value-oriented	High, portfolio alignment
Risk management	Reactive, individualised	Proactive, localised	Systemic, quantitative
Scalability of practices	Limited	Cross-team	Organisational
Dependence on individuals	High	Medium	Low

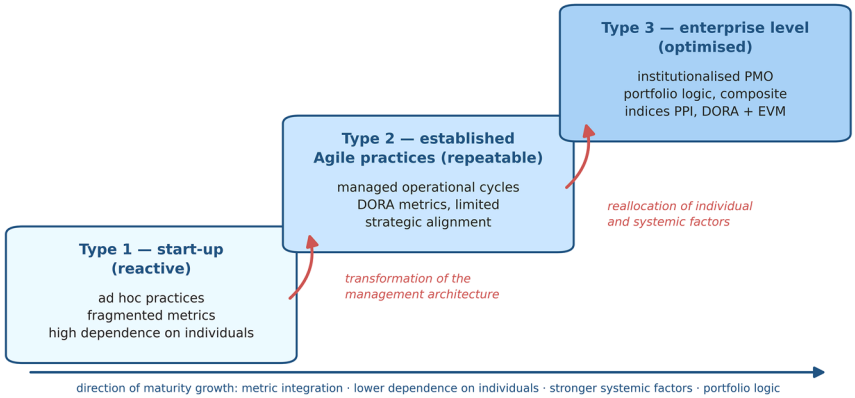

Fig. 1. Conceptual scheme of the non-linear transition between levels of managerial maturity at software development enterprises

Table 2

Intersection of k-means clusters with enterprise size groups ($n = 93$)

k-means cluster	Small ($n = 48$)	Medium ($n = 30$)	Large ($n = 15$)	Interpretation
High-maturity cluster	0	11	15	100 % of large and 36.7 % of medium enterprises
Medium-maturity cluster	8	19	0	63.3 % of medium – transitional type
Low-maturity cluster	40	0	0	83.3 % of small – require transformation

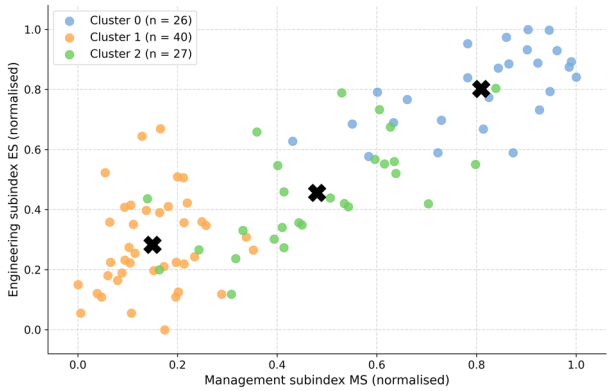

Fig. 2. Cluster analysis of 93 IT enterprises in the two-dimensional space of the MS × ES subindices (centroids marked with X)

correlation and factor analysis. Among the cross-dimensional relationships, the strongest pairs are "process formalisation – CSAT" ($r = 0.71$), "CI/CD – adherence to deadlines" ($r = 0.65$) and "AI readiness – ROI" ($r = 0.53$; all $p < 0.001$). These relationships confirm the synergy of the managerial, engineering and business dimensions of performance. The factorisability of the correlation matrix of the eight project management business processes was confirmed by Bartlett's test ($\chi^2 = 356.13$; $df = 28$; $p < 0.001$). According to the principal component analysis (PCA), the first component explains 56.2 % of the total variance and exhibits high positive loadings (0.67–0.82) across all processes. This indicates the existence of a single latent factor of general managerial maturity and justifies the aggregation of indicators within the PPI subindices; by the Kaiser criterion ($\lambda > 1$) a single principal component was retained.

The calculation of the composite PPI indicator by enterprise group revealed statistically significant differentiation. The mean normalised values are 0.240 for Type 1 enterprises, 0.592 for Type 2 and 0.863 for Type 3 (a gap of ×3.6; ANOVA $F = 82.4$; $df = 2$; 90; $p < 0.001$). The significance of the differences was confirmed across all three subindices.

The quantitative assessment of the determinants of performance was carried out using the regression model specified in the Methodology section; the results are presented in Table 3. The model is characterised by high explanatory power: $R^2 = 0.957$; adjusted $R^2 = 0.951$; $F = 176.57$ ($df_1 = 11$; $df_2 = 81$; $p < 0.001$).

Table 3

Results of estimating the multiple regression model of the PPI (OLS, $n = 93$)

Predictor	Coefficient β	Standard error SE	*t*-statistic	*p*-value
Constant (β_0)	0.4394	0.0707	6.22	<0.001
Size M: medium (relative to large)	–0.1911	0.0207	–9.25	<0.001
Size S: small (relative to large)	–0.4246	0.0332	–12.80	<0.001
Presence of a PMO	+0.0881	0.0141	6.23	<0.001
Use of AI tools	+0.0169	0.0158	1.07	not significant
AI readiness (0–10)	+0.0114	0.0057	2.01	<0.05
CI/CD maturity (0–10)	+0.0260	0.0065	4.02	<0.001
SAFe methodology	+0.0070	0.0259	0.27	not significant
Scrum methodology	+0.0034	0.0173	0.20	not significant

The interpretation of the coefficients supports four conclusions. First, enterprise size is the strongest factor. Other things being equal, the PPI of small enterprises is 0.42 lower and that of medium-sized enterprises 0.19 lower than that of large enterprises ($p < 0.001$). Second, the presence of a PMO adds +0.088 to the PPI ($p < 0.001$). This covers approximately one third of the gap between small and large enterprises and confirms the pivotal role of management institutionalisation. Third, CI/CD maturity (+0.026 per point; $p < 0.001$) and AI readiness (+0.011 per point; $p < 0.05$) exert a statistically significant positive influence, whereas the mere fact of using AI tools without corresponding readiness is not significant. This empirically confirms the moderating rather than autonomous character of the AI effect. Fourth, the methodology applied (Scrum, SAFe and others) is not statistically significant as an isolated factor ($p > 0.05$). This substantiates the contextual nature of methodological choice and the appropriateness of a scenario-based approach to assessing the effects of hybridisation. It is precisely these regression estimates that provide the quantitative foundation for the projected ranges of performance gain used in Scenarios 2 and 3.

The differential economic interpretation of the identified types is as follows. Type 1 enterprises are characterised by a high level of variability in outcomes across key project indicators. This is manifested in a wide dispersion of SPI/CPI values (frequently below 0.9) and unstable profitability figures. Type 2 is distinguished by the transition to managed operational cycles, for which an evening-out of DORA indicators is observed (in particular, deployment frequency and mean time to restore). At the same time, business metrics such as dROI and BRR remain insufficiently developed. Type 3 is marked by mature strategic planning processes, institutionalised benefits management and the full integration of engineering and business metrics within the PPI system. This ensures the predictability of financial results even under external shocks.

Scenario 1 functions as the reference point of the model construct. It records the actual state of project management systems at software development enterprises as of 2024–2025 and reflects local optimisation without a systemic effect. The SPI and CPI indices demonstrate moderate controllability with high variability, while the DORA metrics reflect the partial integration of DevOps practices, predominantly at medium-sized and large companies. Business indicators (revenue per employee, NPS, CSAT, the share of repeat contracts) remain fragmented owing to the absence of end-to-end measurement. The rejection of composite indices in the baseline scenario underlines the key dysfunction of current practice. The disconnect between the managerial, engineering and business circuits leads to the accumulation of technical debt and limits the scalability of managerial decisions.

Scenario 2 models the formalisation of the hybrid methodology. It combines the strengths of the predictive approach (planning discipline, budget control) with those of Agile (adaptability, iterativeness). It thereby ensures the stabilisation of processes in a VUCA environment, together with growing alignment between project activity and corporate strategy. The projected effects are differentiated by enterprise type (Table 4).

In economic terms, the effects of Scenario 2 may be represented as a three-level matrix. At the operational level, a reduction in outcome variability of 15–25 % is expected through the synchronisation of iterative cycles and the standardisation of input data. The regression estimates of the contribution of the PMO (+0.088 to the PPI) and of CI/CD maturity serve as quantitative benchmarks. At the tactical level, an improvement in cost controllability of 10–20 % is projected through the integration of SPI/CPI with the DORA engineering metrics. At the strategic level, institutional readiness is formed for scaling the hybrid model and integrating AI, which lays the foundation for Scenario 3. A key prerequisite for the successful implementation of Scenario 2 is the presence of a PMO acting as an integrator of information flows. Equally important are established organisational rhythms (daily, weekly and quarterly cycles for reviewing key indicators) that ensure the synchronisation of managerial decisions.

Scenario 3 models the substantial influence of analytical and AI tools on an already established hybrid system. The baseline scenario is dominated by the fragmented use of adaptive methods, and Scenario 2 emphasises structural formalisation. By contrast, Scenario 3 treats AI as a catalyst of process maturity rather than an autonomous element of management. The baseline effect values are normalised with reference to the regression estimates of the contribution of AI readiness and to aggregated industry benchmarks: 10 % for the low maturity level, 25 % for the medium level and 40 % for the high level. The ranges (5–25, 20–40, 25–55 %) reflect the uncertainty associated with data quality, integration complexity and organisational resistance. AI does not create a new methodology but reinforces the effect of the hybrid model by providing intelligent support for key processes. The hierarchy of

Table 4

Projected changes in key performance indicators by enterprise type under the scenario of formalising the hybrid methodology [18, 19]

Enterprise type	Controllability of schedules and costs	Variability of outcomes	Alignment with corporate goals
Small (up to 200 employees)	Substantial improvement through standardisation of the hybrid cycle stages	Marked reduction through minimisation of individual deviations	Growth in the share of repeat contracts and client satisfaction
Medium (200–1,000)	Moderate improvement through metric integration in a VUCA environment	Substantial reduction through process stabilisation	Substantial growth through the balance of flexibility and discipline
Large (more than 1,000)	Substantial improvement through systemic integration of large-scale projects	Moderate reduction given the complexity of coordination	Substantial growth through strategic alignment

Table 5

Moderating influence of artificial intelligence tools on the key performance indicators of the hybrid project management model [6, 8]

Maturity level	Reduction in decision-making time, %	Improvement in forecasting accuracy, %	Reduction in managerial risks, %	Principal moderation mechanism	Limiting factors
Low	5–15	5–15	5–20	Limited data integration, detection of baseline deviations	Absence of a quality database, high noise, risk of AI errors
Medium	15–30	10–25	15–35	Automation of routine tasks, basic scenario analysis	Insufficient data standardisation, resistance to change, limited interoperability
High	30–50	20–40	25–45	Synergy with the hybrid model, predictive and prescriptive analytics	Minimal (ethical risks, model updating)

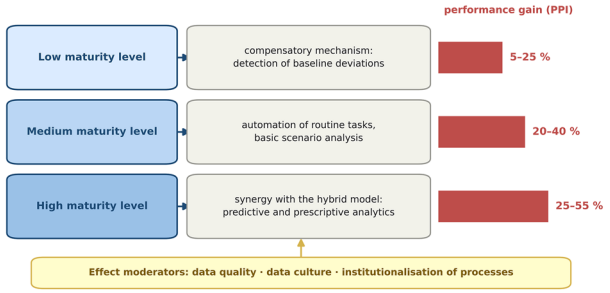

Fig. 3. Model of the moderating influence of artificial intelligence tools depending on the level of managerial maturity of the enterprise

the moderating influence of AI depending on maturity level is presented in Table 5.

A graphical interpretation of the hierarchy of the moderating influence of AI tools is given in Fig. 3. It shows how the level of managerial maturity determines the strength and mechanism of moderation. Moderation is compensatory at the low level, where AI partially substitutes for the absence of data. It becomes synergistic at the high level, where AI amplifies process maturity that is already in place.

The projected differentiation of the AI effect across types of management process is indicative. AI tools exert the greatest influence on risk assessment processes (owing to predictive models based on machine learning), the formation of substantive backlogs (through generative AI) and resource allocation (through optimisation algorithms). Strategic planning and stakeholder management processes remain less sensitive to AI integration, which underlines the moderating rather than substitutive character of the technology. This distinction is important from a managerial standpoint. It enables PMO units to select the sequence of pilot AI initiatives deliberately and to avoid excessive expectations of individual tools.

The adaptive structure of the composite PPI indicator provides for differentiation of the subindex weights, the assessment time horizons and the level of AI integration depending on the level of managerial maturity (Table 6). At the low level the managerial subindex predominates (55–60 %), compensating for process fragmentation through reinforced control. The medium level is characterised by an evening-out of the weights (35–40/30–35/25–30 %) and the formation of a balance between operational efficiency and adaptability. At the high level the business subindex acquires dominant significance (45–55 %), reflecting the transition from reactive control to benefits realisation management. This is consistent with trends in the evolution of performance frameworks.

The process of transforming the management system is described by a four-stage model of the incremental accumulation of managerial maturity. Each successive stage creates the organisational, technical and cultural prerequisites for the realisation of the next. The model is analytical rather than normative in character. It does not establish rigid time frames or a mandatory sequence of actions, but describes a typical trajectory of gradual transition from fragmented practices to an integrated project management system.

The first stage – analytical diagnostics – involves the systematic identification of dysfunctions in the existing management system: gaps between the managerial, en-

Table 6

Differentiation of the parameters of the composite PPI indicator depending on the level of managerial maturity of the enterprise [24, 25]

Maturity level (proxy features)	Dominant management cycle	PPI subindex weights (M/E/B), %	Time horizon	Level of AI integration
Low (SPI/CPI < 0.9; replanning > 30 %; data coverage < 50 %)	Reactive deviation control	55–60/20–25/15–20	Short-term (1–3 months)	Descriptive/ rule-based
Medium (SPI/CPI 0.9–1.1; replanning 10–30 %; data coverage 50–80 %)	Diagnostics and adaptation	35–40/30–35/25–30	Medium-term (3–9 months)	Diagnostic/ scenario-based
High (SPI/CPI > 1.1; replanning < 10 %; data coverage > 80 %)	Predictive planning and benefits realisation	20–30/25–30/45–55	Long-term (9–18 months and beyond)	Predictive/ prescriptive

gineering and business circuits, accumulated technical debt and the fragmentation of metrics. At this stage the baseline maturity level of the enterprise is determined and priority directions for transformation measures are formulated. This provides an evidence base for subsequent managerial decisions.

The second stage – partial integration – encompasses the local introduction of elements of the hybrid methodology within individual teams or programmes. This includes the pilot application of DORA metrics, the basic automation of routine processes and the limited use of artificial intelligence tools for risk forecasting. The key task is to achieve rapid tangible effects and to reduce organisational resistance to change by demonstrating practical results.

The third stage – the scaling of managerial solutions – consists in deploying the hybrid model at the level of the entire enterprise. This is achieved through the cascading of the composite PPI indicator, the centralised use of analytical dashboards and the systematic integration of artificial intelligence into task prioritisation and resource allocation processes. At this stage end-to-end data integration is secured, and a synergistic effect is achieved from the interaction of the managerial, engineering and business subindices.

The fourth stage – stabilisation and control – is characterised by the consolidation of the maturity level attained. It relies on mechanisms of continuous monitoring of benefits realisation, prescriptive analytics, the periodic revision of the PPI weighting coefficients and the institutionalisation of transformation practices. Together these mechanisms ensure the long-term adaptability of the management architecture.

The transition between stages is determined by resource constraints (financial, human and technological) and by the level of managerial maturity. Maturity is operationalised through proxy indicators: the stability of the basic SPI/CPI metrics, the degree of data coverage and the frequency of replanning. Enterprises with a low maturity level may exhibit a protracted transition owing to a shortage of data or organisational resistance, whereas highly mature structures accelerate scaling thanks to a developed infrastructure and data culture. The model allows for cyclicality. In the event of significant exogenous changes, a return to the analytical diagnostics stage is envisaged. This makes the model suitable as a theoretical framework for forecasting the effects of a hybrid methodology in a variety of organisational contexts.

For the quantitative assessment of the level of benefits realisation at portfolio level, the benefits realisation ratio (BRR) indicator is additionally introduced, which acts as one of the key components of the business subindex of the PPI

$$BRR = (\Sigma_i B_i\, actual / \Sigma_i B_i\, planned) \cdot 100\ \%,$$

where B_i actual and B_i planned are, respectively, the actual and planned values of the i^{th} benefit as formalised in the project business case. The BRR is integrated into the PPI as an indicator of the long-term effectiveness of benefits management and is used as one of the key diagnostic signals at the stabilisation stage.

In order to structure the practical implications of the model, Fig. 4 presents a generalised scheme of the cyclical process of managerial decision-making based on the

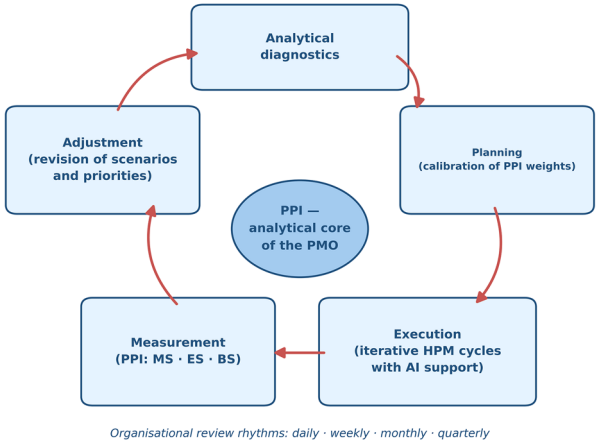

Fig. 4. Cycle of managerial decision-making based on the composite PPI indicator within the hybrid methodology

composite PPI indicator. The scheme demonstrates the interrelationship between diagnostics, planning, execution, measurement and adjustment within the hybrid approach.

The sensitivity of the model to changes in the subindex weighting coefficients was tested by varying the weights within ±10 % and recalculating the resulting PPI value for all three enterprise types. The results of the scenario analysis confirm the structural robustness of the model. Changing the weights within the admissible range does not lead to qualitative changes in the classification of enterprises by maturity level. It also does not disturb the general hierarchy of the moderating influence of AI established in Scenario 3.

A generalised analysis of the results of the empirical study and the scenario modelling allows three key practical conclusions to be formulated. First, enterprises with a higher level of managerial maturity (Type 3) demonstrate substantially greater predictability of key financial and operational indicators and higher resilience to external shocks (pandemics, changes in the regulatory environment, demand turbulence, war). This is manifested in a smaller amplitude of fluctuation in annual revenue growth and margins. Second, Type 2 enterprises, which have already formed a basic set of Agile practices, are the most responsive to the transition to the scenario of formalising the hybrid methodology. It is precisely this group that demonstrates the greatest relative economic return from the systematic integration of metrics without additional technological investment. Third, Type 1 enterprises require above all the analytical diagnostics stage. A premature transition to AI integration without basic process stabilisation increases the risks of entropy and unproductive investment, which is consistent with the barriers to AI adoption identified by S. Salimimoghadam, et al.

The results obtained also make it possible to operationalise the concept of data maturity as a key driver of transformation effects. The threshold at which AI tools begin to deliver a predictably positive performance gain comprises data coverage above 80 %, stable SPI/CPI values within 1.0 ± 0.1, and a replanning frequency below 10 %. Below this threshold the compensatory mechanism predominates. Investment in prescriptive analytics then requires systemic prerequisites: standardised

data sources, documented processes and an enhanced analytical culture within the team.

In order to position the proposed model relative to the widespread frameworks for assessing project management maturity, a comparative analysis was performed (Table 7). Comparison with OPM3, P3M3 and PMMM demonstrates that the proposed construct is the only one that combines empirical verification of the typology, the integration of engineering DORA metrics and a quantitative assessment of the moderating effect of AI. The industry benchmarks of Gartner and McKinsey, for their part, provide aggregated reference points, but do not offer a diagnostic instrument at the level of the individual enterprise.

Conclusions. The research produced the following results. First, a typology of software development enterprises by level of managerial maturity was constructed and empirically verified. It distinguishes three analytical types – start-up (reactive), established Agile practices (repeatable) and mature enterprise level (optimised). The validity of the typology was confirmed by k-means cluster analysis of survey data from 93 Ukrainian IT enterprises (mean silhouette coefficient 0.254). It was further confirmed by the statistically significant differentiation of the composite PPI indicator across groups: 0.240 for the start-up type, 0.592 for the Agile type and 0.863 for the enterprise level (a gap of ×3.6; ANOVA $F = 82.4$; $p < 0.001$). The proposed typology operationalises the non-linearity of the transition between maturity levels and forms a structural basis for the differentiated application of management instruments without recourse to universal solutions.

Second, the determinants of composite project performance were assessed quantitatively by means of a multiple regression model ($R^2 = 0.957$; $p < 0.001$). The statistically significant predictors of the PPI are the presence of a PMO (+0.088), CI/CD maturity (+0.026 per point) and AI readiness (+0.011 per point), whereas the methodology applied is not significant as an isolated factor. This empirically confirms the contextual nature of methodological choice and the moderating character of the effect of AI tools.

Third, a three-level scenario model of the transformation of project management systems was constructed, quantifying the contribution of each stage. The formalisation of the hybrid methodology (Scenario 2) ensures process stabilisation and improved controllability of schedules and costs without additional technological investment. The integration of AI tools (Scenario 3) generates a projected performance gain in the range of 10–40 % depending on the maturity level. The maximum effect is achieved at highly mature enterprises, where synergy between the hybrid model and prescriptive analytics is secured.

Fourth, an adaptive structure of the composite project performance indicator PPI with differentiated subindex weights was developed. At the low maturity level, the managerial subindex predominates (55–60 %); at the medium level the weights are balanced (35–40/30–35/25–30 %). At the high level, the business subindex acquires priority significance (45–55 %), reflecting the transition from reactive control to benefits realisation management. A four-stage transformation model was substantiated (analytical diagnostics – partial integration – scaling – stabilisation). It allows for cyclicality in the event of significant exogenous changes and makes it possible to describe typical transition trajectories with due regard for the resource constraints of the enterprise.

Fifth, the quantitative results of the modelling attest to the economic feasibility of the proposed transformation for all three enterprise types, with a differing distribution of the components of the economic effect. For Type 1 enterprises, the reduction of losses from rework and release delays predominates (up to 60–70 % of the total effect). For Type 2, revenue growth through the stabilisation of project delivery predominates (up to 45–55 % of the effect). For Type 3, the key component is the enhancement of the intangible value of assets through reputational capitalisation, growth in NPS/CSAT and strategic competitive advantage (up to 40–50 % of the effect). This distribution illustrates the evolution of the economic logic of transformation from a compensatory to a value-oriented rationale, and is consistent with the concept of benefits realisation management.

The proposed model may be used by PMO units and the top management of software development enterprises as an applied multifunctional instrument. It provides for: 1) diagnostics of the actual level of managerial maturity by proxy indicators (SPI/CPI, data coverage, replanning frequency) and the selection of a relevant

Table 7

Comparison of the proposed model with existing project management maturity assessment frameworks [4, 5]

Comparison criterion	OPM3 (PMI)	P3M3	PMMM (Kerzner)	Proposed model
Nature of assessment	Descriptive, s elf-assessment of practices	Descriptive, five maturity levels	Normative, five levels	Quantitative, empirically verified (clustering, OLS regression)
Differentiation by enterprise type	Absent (universal approach)	Absent	Limited	Three types with adaptive subindex weights
Integration of engineering metrics (DORA, CI/CD)	Absent	Absent	Absent	Full (ES subindex)
Link to business results	Indirect	Indirect	Limited	Direct (BS subindex: dROI, BRR, NPS/CSAT), regression validation
Treatment of the role of AI	Absent	Absent	Absent	Moderating effect, quantitatively estimated
Predictive capability	Low	Low	Medium	Scenario forecasts with quantitative ranges

management profile; 2) substantiation of the sequence and priorities of transformation measures with minimisation of organisational resistance; 3) calibration of the PPI metric system to a specific enterprise type without loss of comparability of results; 4) investment decision-making concerning the adoption of AI tools with due regard for the prerequisites relating to data and process maturity. The latter makes it possible to avoid the common situation in which a considerable share of organisations obtains no return from AI initiatives because the basic integration prerequisites are absent. For investors and strategic partners, the model provides a quantitative rationale for the economic feasibility of investment in transformation projects by demonstrating positive NPV and IRR at or above industry standards.

By comparison with the existing approaches (Table 7), the proposed model possesses three substantial methodological advantages. First, unlike universal maturity models (OPM3, P3M3), it differentiates the assessment parameters by enterprise type. This makes it possible to avoid the formal copying of instruments in companies with fundamentally different levels of process maturity. Second, unlike classical models of AI impact, in which the technology is treated as an independent variable, the model explicitly accounts for the interaction character of the effect of AI tools. This is empirically confirmed by the non-significance of the fact of AI use alongside the significance of AI readiness. Third, the integration of the four-stage transformation scheme with an adaptive PPI creates the possibility of managing the trajectory of maturity growth rather than merely recording its current state.

Further research prospects are associated with the empirical validation of the model on panel data from Ukrainian and international IT companies. This concerns longitudinal studies covering the period 2026–2030 with due regard for the post-pandemic recovery cycle and regulatory changes, in particular the requirements of the EU AI Act. Promising directions also include the development of technical specifications for AI modules for the automated cascading of the PPI. A further direction is the adaptation of the toolkit to other segments of the KIBS-sector – consulting, fintech and R&D enterprises with similar profiles of project intensity and a predominance of intangible assets. A separate direction is the integration of the proposed model with corporate ESG metrics. This would make it possible to extend the business subindex of the PPI through indicators of social and environmental responsibility relevant to contemporary investors in the KIBS-sector.

References.

1. Reiff, J., & Schlegel, D. (2022). Hybrid project management – a systematic literature review. *International Journal of Information Systems and Project Management, 10*(2), 45-63. https://doi.org/10.12821/ijispm100203

2. Khan, U., & Qaiser, M. (2025). Hybrid project management and its effects on project performance. *International Journal of Organization Theory & Behavior*, 1-18. https://doi.org/10.1108/IJOTB-09-2024-0166

3. Bianca, B., & Hanslo, R. (2025). *The evolution of Agile and Hybrid project management methodologies: A systematic literature review. arXiv:2511.02859*. https://doi.org/10.48550/arXiv.2511.02859

4. Fabbro, E., & Tonchia, S. (2021). Project management maturity models: Literature review and new developments. *The Journal of Modern Project Management, 8*(3), 34-45. https://doi.org/10.19255/JMPM02503

5. Mahdi, E. (2025). Project management maturity in project-based organizations: Frameworks, drivers, and the role of sustainability. *Future Business Journal, 11*, 245. https://doi.org/10.1186/s43093-025-00670-z

6. Almeida, P. M., Fernandes, G., & Santos, J. M. R. C. A. (2025). Artificial intelligence tools for project management: A knowledge-based perspective. *Project Leadership and Society, 6*, 100196. https://doi.org/10.1016/j.plas.2025.100196

7. Salimimoghadam, S., Ghanbaripour, A. N., & Tumpa, R. J. (2025). The rise of artificial intelligence in project management: A systematic literature review of current opportunities, enablers, and barriers. *Buildings, 15*(7), 1130. https://doi.org/10.3390/buildings15071130

8. Hughes, L., Mavi, R. K., & Aghajani, M. (2025). Impact of artificial intelligence on project management (PM): Multi-expert perspectives on advancing knowledge and driving innovation toward PM2030. *Journal of Innovation & Knowledge, 10*(3), 100772. https://doi.org/10.1016/j.jik.2025.100772

9. Pham, K. P., & Neumann, M. (2024). *How to measure performance in Agile software development? A mixed-method study. arXiv:2407.06357*. https://doi.org/10.48550/arXiv.2407.06357

10. Piliukov, A. O. (2024). Comparative analysis of theories and approaches to project management. *Kyiv Economic Scientific Journal*, (5), 114-121. https://doi.org/10.32782/2786-765X/2024-5-17

11. Piliukov, A. O. (2026). Conceptual basis of project management of software development enterprises. *Economic Bulletin of National Technical University of Ukraine "Kyiv Polytechnic Institute"*, (36), 101-108. https://doi.org/10.20535/2307-5651.36.2026.360552

12. Song, L., & Minku, L. L. (2023). *Artificial intelligence in software project management*. Springer. https://doi.org/10.1007/978-3-031-19701-2

13. Diameh, J. T., Bakare, T. O., Daniels, C., Okopido, E. S., Nelson, C. A., & Quaye, M. (2025). Integrating AI-driven predictive analytics in project risk management to optimize decision-making and performance efficiency. *International Journal of Engineering Technology Research & Management, 9*(3), 373-387. https://doi.org/10.5281/zenodo.15086329

14. Forouzesh Nejad, A. A., Arabikhan, F., & Gegov, A. (2025). Data-driven predictive modelling of agile projects using explainable artificial intelligence. *Electronics, 14*(13), 2609. https://doi.org/10.3390/electronics14132609

15. Oftebro, K. L., Nguyen-Duc, A., & Kemell, K.-K. (2025). *GenAI-enabled backlog grooming in agile software projects: An empirical study. arXiv:2507.10753*. https://doi.org/10.48550/arXiv.2507.10753

16. Geamanu, A., Dascalu, M.-I., Neagu, A.-M., & Guica, R. I. (2026). An integrated artificial intelligence tool for predicting and managing project risks. *Machine Learning and Knowledge Extraction, 8*(1), 1. https://doi.org/10.3390/make8010001

17. Leite, G. S., Vieira, R. E. P., Cerqueira, L., Maciel, R. S. P., Freire, S., & Mendonça, M. (2024). Technical debt management in Agile software development: A systematic mapping study. *Proceedings of the XXIII Brazilian Symposium on Software Quality*, (pp. 309-320). https://doi.org/10.1145/3701625.3701669

18. Zaman, U., Khan, M. N., Raza, S. H., & Farías, P. (2022). Fall seven times, stand up eight: Linking project management innovation, project governance, and high-performance work practices to project success. *Frontiers in Psychology, 13*, 902816. https://doi.org/10.3389/fpsyg.2022.902816

19. Moura, R. L., Carneiro, T. C. J., & Dias, T. L. (2023). VUCA environment on project success: The effect of project management methods. *Brazilian Business Review, 20*(3), 237-256. https://doi.org/10.15728/bbr.2023.20.3.1.en

20. Serra, C. E. M., & Kunc, M. (2015). Benefits realisation management and its influence on project success and on the execution of business strategies. *International Journal of Project Management, 33*(1), 53-66. https://doi.org/10.1016/j.ijproman.2014.03.011

21. Iriarte, C., & Bayona, S. (2020). IT projects success factors: A literature review. *International Journal of Information Systems and Project Management, 8*(2), 49-78. https://doi.org/10.12821/ijispm080203

22. Alexandru, V. A., Bolisani, E., Andrei, A. G., Cegarra-Navarro, J. G., Martínez Martínez, A., Paiola, M., ..., & Zieba, M. (2020). Knowledge management approaches of small and medium-sized firms: A cluster analysis. *Kybernetes, 49*(1), 73-87. https://doi.org/10.1108/K-03-2019-0211

23. Slávik, Š., Bednár, R., Mišúnová Hudáková, I., & Moravčíková, K. (2020). Cluster typology of business models of start-ups. *Administrative Sciences, 10*(3), 54. https://doi.org/10.3390/admsci10030054

24. Frish, S., Talmor, I., Hadar, O., Shoshany, M., & Shapira, A. (2025). Enhancing consistency of AHP-based expert judgements:

A new approach and its implementation in an interactive tool. *MethodsX, 14*, 103341. https://doi.org/10.1016/j.mex.2025.103341
25. Yadav, N., Sushil, & Sagar, M. (2013). Performance measurement and management frameworks: Research trends of the last two decades. *Business Process Management Journal, 19*(6), 947-971. https://doi.org/10.1108/BPMJ-01-2013-0003
26. Gobov, D., & Zuieva, O. (2025). Software quality attributes in requirements engineering. *International Journal of Information Technology and Computer Science, 17*(4), 38-48. https://doi.org/10.5815/ijitcs.2025.04.04
27. Savitri, N. K. W., Sandhiyasa, I. M. S., Fittryani, Y. P., Sudipa, I. G. I., & Putra, D. M. D. U. (2025). Design of real-time project monitoring dashboard using Kimball's data warehouse approach and Google Data Studio. *Sinkron: Jurnal dan Penelitian Teknik Informatika, 9*(3), 1050-1060. https://doi.org/10.33395/sinkron.v9i3.14801

Моделювання впливу гібридної методології на результативність IT-підприємств

*М. В. Босовська, А. О. Пілюков**
Державний торговельно-економічний університет, м. Київ, Україна
* Автор-кореспондент e-mail: a.pilyukov@knute.edu.ua

Мета. Розроблення й емпірична верифікація модельного підходу до оцінювання впливу гібридної методології управління проєктами на результативність підприємств із розробки програмного забезпечення з урахуванням рівня управлінської зрілості й модерувальної ролі інструментів штучного інтелекту.

Методика. Дослідження ґрунтується на результатах авторського анкетування 93 українських IT-підприємств (2026 р.) і поєднує кластерний аналіз (алгоритм k-means із силуетним критерієм якості), множинне регресійне моделювання (OLS), метод аналітичної ієрархії (AHP) з перевіркою узгодженості експертних оцінок (CR < 0,1) і трирівневе сценарне моделювання. Типологія підприємств сформована за рівнем управлінської зрілості на основі агрегування управлінських, інженерних і бізнесових показників.

Результати. Емпірично підтверджена типологія з трьох типів підприємств: стартапний, зі сформованими Agile-практиками та зрілий enterprise-рівень. Регресійна модель (R^2 = 0,957) засвідчила статистично значущий вплив наявності проєктного офісу, зрілості CI/CD і ШІ-готовності на інтегральний показник результативності проєктів (PPI). Обґрунтована трансформація системи управління через три сценарії: базовий, формалізація гібридної методології та інтеграція інструментів штучного інтелекту. Запропонована адаптивна структура PPI із диференційованими вагами субіндексів і часовими горизонтами оцінювання; отримано прогнозний приріст результативності в діапазоні 10–40 % із максимумом на високозрілих підприємствах.

Наукова новизна. Розроблена та емпірично верифікована багаторівнева модель оцінювання впливу гібридної методології управління проєктами, що, на відміну від описових моделей зрілості, поєднує типологію підприємств за управлінською зрілістю, адаптивний інтегральний показник PPI і чотириетапну схему трансформації управлінських практик. Модель операціоналізує нелінійність переходу між рівнями зрілості з урахуванням модерувальної ролі ШІ-інструментів і ресурсних обмежень підприємства.

Практична значимість. Запропонована модель має на меті бути аналітичним інструментом для обґрунтування управлінських рішень щодо впровадження гібридної методології й інтеграції штучного інтелекту на підприємствах із розробки програмного забезпечення. Її застосування забезпечує прогнозовано позитивний економічний ефект через скорочення втрат, зростання доходів і підвищення нематеріальної цінності активів, а також формує кількісне обґрунтування інвестиційних рішень через демонстрацію позитивного NPV та IRR.

Ключові слова: *гібридна методологія, управління проєктами, інтегральний показник PPI, штучний інтелект, IT-підприємства*