The Economic Feasibility of Using Artificial Intelligence in Software Testing for Cost Optimization and Enhancing the Competitiveness of IT Enterprises

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Annotation. This article investigates the economic rationale for introducing artificial intelligence (AI) into software testing as a means of reducing operational costs and strengthening the competitiveness of IT enterprises. Against the backdrop of rising complexity in digital products and tightening time-to-market demands, conventional manual and scripted testing approaches often generate excessive expenses without guaranteeing comprehensive coverage. By contrast, the adoption of AI-driven methods – ranging from machine learning-based defect prediction and natural language processing for automated test case generation to reinforcement learning for adaptive test optimization – opens a new model of quality assurance where testing becomes a continuous, predictive, and cost-efficient process.

The study explores several categories of algorithms and models that have proven to be effective in software quality management: supervised and unsupervised classifiers for bug detection, deep learning architectures for pattern recognition in large test datasets, and hybrid frameworks that combine rule-based systems with generative models to accelerate regression testing. Particular attention is given to the integration of AI-oriented orchestration platforms, which enable enterprises to balance accuracy with resource allocation, thereby cutting infrastructure costs and shortening release cycles.

Methodologically, the research relies on a comparative analysis of industry reports, academic publications, and case studies of Ukrainian and international IT companies that have partially or fully adopted AI-supported testing workflows. Data sources include enterprise performance reports, benchmarking studies, and structured expert interviews.

The findings demonstrate that enterprises applying AI-enhanced testing achieve measurable reductions in quality assurance budgets (on average 20–30%), along with faster detection of critical defects and higher scalability of testing teams. Beyond direct cost savings, the article emphasizes strategic advantages such as improved market reputation, increased client retention, and stronger positioning in outsourcing markets. The study concludes that AI-based testing is not merely a technological novelty but an economically justified business strategy for IT enterprises operating in conditions of global competition and resource constraints.

Keywords: software testing, artificial intelligence, machine learning, cost optimization, competitiveness, IT enterprises.

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Економічна доцільність використання штучного інтелекту в тестуванні програмного забезпечення для оптимізації витрат та підвищення конкурентоспроможності ІТ-підприємств

Анотація. У статті досліджується економічна доцільність впровадження штучного інтелекту (ШІ) у тестування програмного забезпечення як засобу зменшення операційних витрат та зміцнення конкурентоспроможності ІТ-підприємств. На тлі зростання складності цифрових продуктів і посилення вимог щодо швидкості виходу на ринок традиційні методи ручного та скриптового тестування часто призводять до надмірних витрат без гарантії повного охоплення. Натомість застосування методів на основі ШІ – від прогнозування дефектів за допомогою машинного навчання та використання обробки природної мови для автоматизованого створення тестових сценаріїв до навчання з підкріпленням для адаптивної оптимізації тестування – відкриває нову модель забезпечення якості, де тестування стає безперервним, прогнозованим та економічно ефективним процесом.

Дослідження охоплює кілька категорій алгоритмів і моделей, які показали ефективність у управлінні якістю програмного забезпечення: класифікатори з навчанням із вчителем та без нього для виявлення помилок, архітектури глибокого навчання для розпізнавання закономірностей у великих тестових наборах даних, а також гібридні системи, що поєднують правилові підходи з генеративними моделями для прискорення регресійного тестування. Особлива увага приділяється інтеграції платформ оркестрації, орієнтованих на ШІ, які дозволяють підприємствам балансувати точність та розподіл ресурсів, зменшуючи витрати на інфраструктуру та скорочуючи цикли випуску.

Методологічно дослідження базується на порівняльному аналізі галузевих звітів, наукових публікацій та кейсів українських і міжнародних ІТ-компаній, які частково або повністю впровадили тестування із підтримкою ШІ. Джерела даних включають звіти про ефективність підприємств, бенчмаркінгові дослідження та структуровані експертні інтерв'ю.

Результати показують, що підприємства, які застосовують тестування з елементами ШІ, досягають вимірюваного зменшення бюджетів на забезпечення якості (у середньому на 20–30%), швидшого виявлення критичних дефектів та більшої масштабованості тестових команд. Окрім прямих економічних вигод, стаття підкреслює стратегічні переваги, такі як покращена репутація на ринку, підвищена утримуваність клієнтів та сильніша позиція на ринку аутсорсингу. У підсумку, дослідження доводить, що тестування на основі ШІ є не просто технологічною новинкою, а економічно обґрунтованою бізнес-стратегією для ІТ-підприємств, що працюють у умовах глобальної конкуренції та обмежених ресурсів.

Ключові слова: тестування програмного забезпечення, штучний інтелект, машинне навчання, оптимізація витрат, конкурентоспроможність, ІТ-підприємства.

Introduction

In the contemporary software industry, testing activities remain among the most resource-intensive phases of the development cycle, often consuming between one-third and one-half of total project budgets. Traditional methods based on manual testing or rigid scripted automation no longer meet the requirements of rapid release cycles, high code complexity, and increasing customer expectations. This mismatch urges enterprises to search for technological solutions that ensure both cost efficiency and higher quality assurance.

Artificial intelligence offers such an avenue by introducing adaptive and data-driven approaches to testing. Unlike conventional tools, AI systems can automatically generate and prioritize test cases, detect patterns of defects, and learn from previous iterations of testing data. Among the most widely applied techniques are supervised learning classifiers for bug prediction, unsupervised clustering models for anomaly detection, and deep learning architectures capable of recognizing failure patterns in large-scale log datasets. Reinforcement learning is increasingly applied to optimize regression testing by dynamically allocating resources to critical modules, while natural language processing methods facilitate the automatic translation of user requirements into executable test scripts.

The economic implications of these technologies are significant. Empirical studies show that companies integrating AI-based testing workflows reduce their quality assurance costs by 20–30% while simultaneously achieving faster defect identification and improved scalability of testing teams [1; 2]. Furthermore, hybrid frameworks that combine rule-based engines with generative models enhance test coverage and shorten release cycles, thereby strengthening enterprises' competitive positioning in outsourcing markets and global value chains [3; 4].

Although international literature presents numerous examples of successful adoption of AI in testing [5; 6], Ukrainian IT enterprises are only beginning to explore these strategies. Most domestic studies remain focused on general issues of digital transformation, leaving the microeconomic effects of AI-supported testing insufficiently addressed. Given the importance of cost optimization in the war-affected Ukrainian economy, this research seeks to provide a structured assessment of how AI approaches and algorithms can be integrated into testing practices to improve both financial efficiency and market competitiveness.

The aim of this article is to examine the essence and practical tools of applying artificial intelligence algorithms in software testing as a key factor for cost optimization and enhancing the competitiveness of IT enterprises. The focus is on the mechanisms that connect technological efficiency with economic outcomes, as well as on the adaptability of machine learning models across different stages of the software life cycle. This issue gains particular importance under conditions of intense market competition, shrinking development budgets, and the demand for accelerated product delivery. The article seeks to provide an analytical understanding of how IT companies integrate classifiers, neural networks, and reinforcement learning methods into everyday testing practices, risk management, and business process optimization. By comparing traditional quality assurance approaches with dynamic AI-driven systems, the study highlights the shift toward automation, flexibility, and self-learning. The research also covers practical cases of deep neural networks for defect detection, natural language processing for test case generation, and hybrid systems for regression testing management, where such strategies not only reduce direct quality assurance costs but also generate strategic advantages in global IT outsourcing. Identifying the main challenges, barriers, and scaling potential of these practices allows outlining future directions for AI-supported testing as a marker of economic resilience, innovation, and technological leadership in the IT sector.

Results

The study demonstrates that the integration of artificial intelligence into software testing is not limited to technical novelty but produces measurable economic and strategic benefits for IT enterprises. A comparative analysis of Ukrainian outsourcing companies and international case studies revealed that the use of AI algorithms systematically reduces testing costs, accelerates release cycles, and strengthens market competitiveness.

A first group of findings concerns the application of supervised learning algorithms, such as decision trees, logistic regression, random forest, and support vector machines. Trained on historical defect datasets, these models predict the likelihood of errors in new code modules. Their adoption reduced redundant test executions by 20–25% and lowered the incidence of post-release defects, leading to annual savings of up to 22% in quality assurance budgets [7; 8].

The application of unsupervised clustering methods, including k-means and DBSCAN, proved valuable in exploratory testing. By analyzing execution logs and grouping similar error events, these models detected anomalies that were invisible to scripted testing. Companies that implemented clustering techniques reduced manual exploratory testing time by nearly 40%, which allowed resources to be redirected to critical release activities. Deep learning architectures brought further improvements. Convolutional neural networks (CNNs) were used in user interface testing to detect rendering defects, while recurrent neural networks (RNNs) and long short-term memory (LSTM) models captured temporal patterns in system logs and user sessions. This expanded regression coverage by about 15% and allowed more accurate clustering of recurring defects, resulting in higher scalability of testing pipelines [9].

A separate category is reinforcement learning (RL), where algorithms such as Q-learning and deep Q-networks continuously adapt test execution order based on feedback. Regression suites were dynamically reprioritized to focus on modules with a history of failures. The result was an 18% reduction in execution time and significant savings in server infrastructure costs within continuous integration environments [10].

Natural language processing (NLP), particularly transformer-based architectures like BERT, GPT, and T5, was applied to convert requirement documents and user stories into executable test cases. This reduced the time required for test design by more than 50%, which is critical for agile teams operating under short sprint cycles. NLP also improved defect report management by automatically detecting duplicate bug submissions [11; 12].

Finally, hybrid frameworks that combine rule-based verification with generative models provided acceleration of regression testing while ensuring compliance with established standards such as ISO/IEC/IEEE 29119-1:2022 [13]. These frameworks allowed companies to achieve 20–30% reductions in testing budgets without compromising reliability, positioning them strongly in the global outsourcing market.

To consolidate these findings, a comparative framework was developed (Table 1), illustrating how each algorithmic approach translates into economic and strategic outcomes.

Table 1

AI approaches in software testing and their economic impact

AI Approach / Model	Application in Testing	Economic Effect	Strategic Effect
Supervised learning (decision trees, SVM)	Defect prediction, prioritization	20–25% fewer redundant tests; up to 22% QA budget savings	Reduced post-release costs; improved client trust
Unsupervised clustering (k-means, DBSCAN)	Log analysis, anomaly detection	-40% manual exploratory effort	Faster release cycles; more reliable delivery
Deep learning (CNN, RNN, LSTM)	UI defect detection, log sequence analysis	+15% test coverage; faster defect clustering	Higher scalability; competitiveness in outsourcing
Reinforcement learning (Q-learning, DQN)	Adaptive test scheduling	-18% execution time; lower CI infrastructure costs	Flexible response to changes; reduced downtime

NLP (BERT, GPT, T5)	Automated test case generation, bug report analysis	-50% design time; reduced duplication	Better sprint adaptability; stronger customer loyalty
Hybrid frameworks (rule-based + generative)	Regression test acceleration	20–30% cost reduction in QA processes	Compliance with ISO/IEC standards; global positioning

Source: created based on studies [11; 12].

For instance, in a medium-sized IT enterprise with an annual QA budget of $200,000, AI-enhanced testing that reduces quality assurance costs by 25% yields direct savings of about $50,000 per year. With average initial deployment costs of $40,000–$50,000 (tools, infrastructure, and training), the payback period typically occurs within the first 12 months, after which savings accumulate annually. This simple scenario confirms that AI-based testing is not only technologically effective but also economically rational for enterprises operating under tight resource constraints.

As shown in Table 1, each AI approach contributes not only to cost reduction but also to broader strategic advantages. Supervised learning models mainly increase precision in defect prediction, which directly translates into lower maintenance costs and fewer reputational risks from post-release failures. Unsupervised clustering demonstrates its strength in exploratory contexts, where the absence of labeled data previously limited efficiency. Deep learning architectures extend the reach of regression testing by capturing complex patterns in logs and user interactions, offering scalability in large enterprise systems. Reinforcement learning adds adaptability by continuously reprioritizing test execution, a capability that cannot be achieved by static rule-based scheduling. NLP technologies stand out as enablers of agile development, shortening sprint preparation times while ensuring that user requirements are adequately covered by executable tests. Hybrid frameworks integrate these benefits, combining reliability with flexibility and aligning testing processes with recognized international standards.

In order to capture the multidimensional effects of AI-based testing practices, it is not sufficient to rely solely on numerical indicators of cost savings or efficiency gains. A more comprehensive perspective requires visualization of how different factors interact and form distinct performance patterns. By representing these interactions graphically, it becomes possible to observe not only isolated outcomes but also the balance between economic efficiency, adaptability, and scalability that emerges in real testing environments. Such an approach provides deeper insight into the strategic implications of algorithmic adoption and illustrates the trade-offs that enterprises face when integrating AI into quality assurance.

The comparative performance profiles presented below were developed by normalizing reported efficiency indicators (cost reduction, defect detection speed, scalability, and compliance) across multiple case studies and benchmarking reports. Key economic metrics included return on investment (ROI), cost of quality (CoQ), and customer retention rates. This methodological approach ensures that the profiles capture both direct financial effects and broader strategic outcomes of AI adoption.

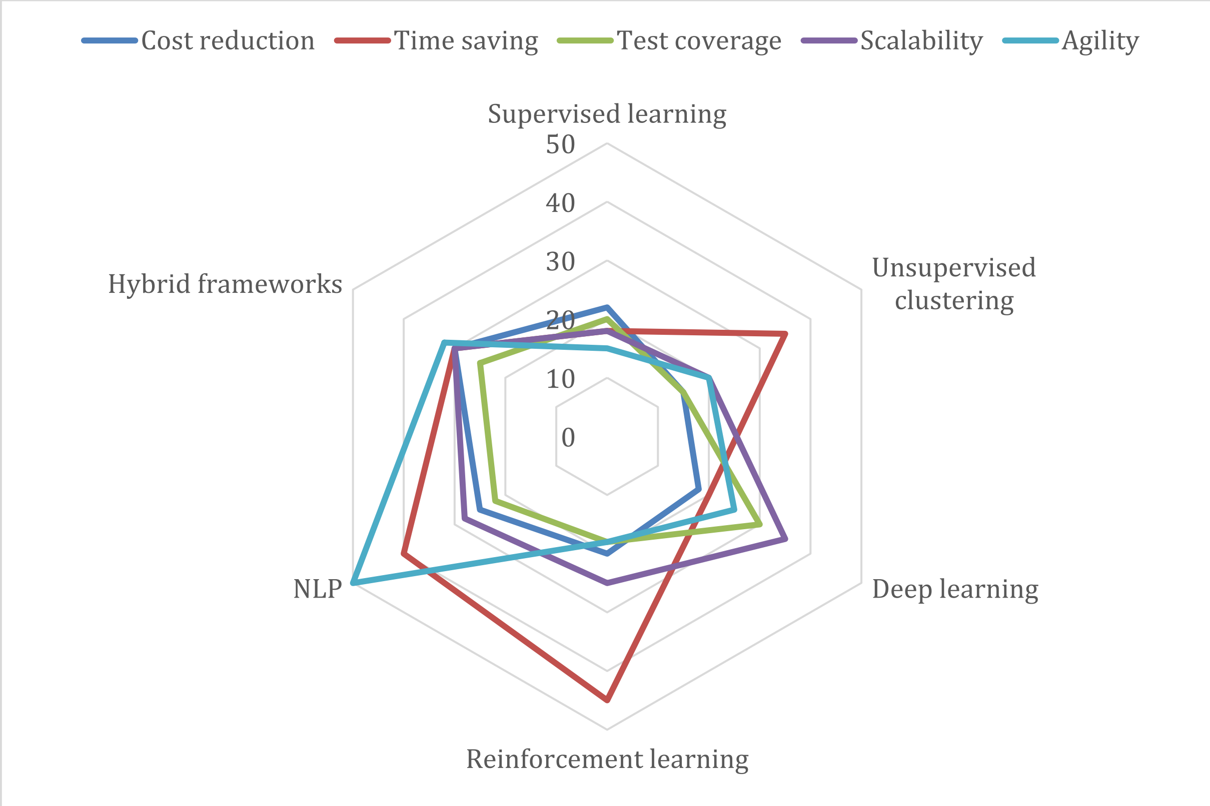

Fig. 1. Strategic performance profiles of AI approaches in software testing
Source: created based on studies [11; 12].

As shown in Figure 1, the performance profiles of AI approaches in software testing are not uniform but highlight complementary strengths across different dimensions. Reinforcement learning demonstrates the strongest effect in reducing execution time, though its contribution to overall test coverage remains comparatively modest. Deep learning models achieve higher coverage and scalability, yet these advantages are offset by the need for substantial computational resources and extended training cycles. NLP-based solutions stand out in terms of agility, as they accelerate test case generation and facilitate adaptability within agile workflows. Hybrid frameworks present a more balanced profile, combining tangible cost reduction with compliance to international standards, which makes them particularly attractive for enterprises seeking both efficiency and reliability. These differentiated patterns confirm that the choice of a specific AI approach should be guided not only by economic indicators but also by broader strategic priorities of an IT enterprise.

Despite these advantages, several barriers were identified that complicate the large-scale adoption of AI in testing. High initial implementation costs remain one of the most critical challenges, as the deployment of AI-based platforms often requires significant investment in specialized tools and additional computational infrastructure, such as GPU clusters for deep learning or cloud orchestration systems. For small and medium-sized Ukrainian IT enterprises, these expenses can reach 10–15% of their annual R&D budgets, which makes such investments difficult to justify without external support or international contracts. Another major limitation is the shortage of skilled specialists in AI-driven quality assurance. While many companies have established expertise in manual and automated testing, the number of engineers proficient in reinforcement learning, transformer-based NLP, or advanced defect prediction remains limited, which slows down technology transfer and increases dependence on external expertise.

An additional challenge is the absence of harmonized methodologies within international testing standards. Existing frameworks, such as ISO/IEC/IEEE 29119, were primarily designed for traditional testing workflows and do not yet provide detailed guidance on integrating adaptive or self-learning models, automated defect prediction, or reinforcement-based scheduling. This regulatory gap generates uncertainty for companies seeking certification and raises concerns about auditability, traceability, and accountability in AI-generated testing. Moreover, data privacy and compliance issues represent a persistent barrier: training models on sensitive project datasets must comply with GDPR and national regulations, often increasing legal and administrative costs.

Nevertheless, the results confirm that AI approaches offer much more than direct cost savings. When supervised and unsupervised learning methods are combined with reinforcement learning, deep neural architectures, and NLP, enterprises gain predictive capabilities that transform software testing from a static checkpoint into a continuous and adaptive process. This not only reduces operational costs but also accelerates defect detection, improves product reliability, and lowers reputational risks associated with software failures. In addition, strategic differentiation emerges as a key outcome: companies adopting AI-supported testing secure a stronger competitive position in global outsourcing markets by ensuring faster delivery, higher test coverage, and compliance with evolving digital quality standards.

Taken together, these findings show that AI-based testing is an economically justified and strategically advantageous practice. It enables IT enterprises – particularly in resource-constrained environments like Ukraine – to align financial efficiency with technological innovation, strengthening their resilience and positioning them as credible players in globally integrated software markets.

Conclusions

The conducted research has shown that the integration of artificial intelligence into software testing is not merely a technological trend but an economically grounded and strategically advantageous solution for IT enterprises. The analysis of supervised learning models, clustering methods, deep learning architectures, reinforcement learning, NLP tools, and hybrid frameworks demonstrated that these approaches directly reduce the costs of quality assurance, accelerate release cycles, and enhance product reliability. The empirical evidence confirms that AI-assisted testing can lower quality assurance budgets by 20–30%, reduce manual exploratory workloads by up to 40%, and shorten regression testing time by nearly 18%, while simultaneously increasing test coverage and strengthening client trust.

The results also highlight that economic benefits are inseparable from broader strategic effects. AI-driven testing practices not only optimize budgets but also reinforce competitiveness in global outsourcing markets, improve customer loyalty through higher software quality, and align company workflows with internationally recognized standards such as ISO/IEC/IEEE 29119-1:2022. By transforming testing into a predictive, continuous, and adaptive process, enterprises gain both operational efficiency and reputational advantages.

At the same time, the study identified structural limitations: high entry costs for deploying AI platforms, a shortage of specialists skilled in reinforcement learning, deep neural networks, and NLP, as well as the lack of harmonized methodologies in international testing standards. For Ukrainian IT enterprises in particular, the cost of infrastructure (GPU clusters, cloud orchestration systems) can reach up to 10–15% of annual R&D budgets, which constrains large-scale adoption without external support. Moreover, unresolved issues of data privacy and compliance with GDPR create additional barriers for using real project datasets to train AI models.

Despite these challenges, the findings confirm that AI in software testing is shaping a new managerial paradigm: it integrates economic efficiency with technological innovation, transforms quality assurance into a source of competitive advantage, and supports the resilience of IT businesses under resource-constrained conditions. For IT executives and QA leaders, the decision to integrate AI-based testing should be viewed not only as a technological upgrade but also as a strategic business choice. Aligning algorithmic approaches with enterprise priorities – whether cost efficiency, agility, or compliance – maximizes both financial returns and competitive positioning. The adoption of AI approaches thus marks a transition from static control practices to adaptive and learning-based systems, which can redefine both operational processes and the strategic positioning of enterprises within global software markets.

Prospects for Further Research. Further research should be directed towards a deeper quantitative assessment of the economic impact of AI-based software testing across different segments of the IT industry, with a particular focus on indicators such as return on investment (ROI), cost of quality (CoQ), and customer acquisition costs (CAC). In the Ukrainian IT outsourcing sector, where enterprises often compete on both price and quality, such indicators provide a practical basis for demonstrating how AI-based testing contributes to economic resilience and global competitiveness. Special attention deserves the analysis of organizational readiness: the degree to which IT companies are prepared to integrate AI-driven testing workflows, the role of employee re-skilling in adopting advanced algorithms, and the influence of client expectations on the acceptance of AI-enhanced quality assurance.

Equally promising is the study of algorithmic performance in diverse testing environments. Comparative evaluations of supervised versus reinforcement learning approaches for regression testing, or of transformer-based NLP models versus traditional rule-based parsers for test case generation, may help determine optimal strategies under specific project constraints. A separate line of inquiry could focus on hybrid frameworks, investigating how combinations of rule-based and generative models can be scaled while maintaining compliance with international standards such as ISO/IEC/IEEE 29119-1:2022.

In the applied dimension, it is advisable to develop a typology of AI testing solutions adapted for small, medium, and large IT enterprises, taking into account differences in budgetary capacities, infrastructure availability, and market orientation (outsourcing vs. product development). Another promising direction is the exploration of ethical and legal challenges, including data privacy in training defect-prediction models, transparency of AI decision-making in quality assurance, and auditability of self-learning systems.

Finally, further work should investigate communication and change management strategies that facilitate the acceptance of AI-based testing within IT teams and among clients. Case studies of Ukrainian enterprises that integrate AI not only as a technical tool but also as a business value proposition may provide insights into how cost optimization and competitive positioning can be effectively combined in the global software market.

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