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METHODS OF USING ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN THE CONTEXT OF DIGITALIZATION

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Abstract

This article examines methods for using artificial intelligence technologies under conditions of economy-wide digitalization, with a focus on applications relevant to an economic university context. The central argument is that effective AI adoption is not defined by the presence of algorithms alone, but by the quality of methodical integration across data governance, process redesign, human capital development, and institutional decision-making. The paper conceptualizes AI methods as an operational toolkit that includes predictive analytics for forecasting demand and risks, machine learning for credit scoring and anomaly detection, natural language processing for document management and customer interaction, computer vision for compliance and asset monitoring, and generative AI for knowledge work support in analysis, reporting, and academic writing. Particular attention is paid to the “method layer” that connects technologies with measurable outcomes: defining use cases, specifying performance metrics, ensuring data quality, controlling bias, and establishing responsible-use safeguards. The study also emphasizes the need for organizational methods such as pilot-based implementation, MLOps practices for lifecycle management, interdisciplinary project teams, and competency-based training for students and staff. In the context of Uzbekistan’s digital transformation agenda, the article highlights pragmatic pathways for integrating AI into economic education and practice through applied laboratories, industry datasets, simulation cases, and institutional

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analytics. The expected contribution is a structured, practice-oriented model that helps universities and economic organizations select AI methods, implement them responsibly, and evaluate results in terms of productivity, service quality, and decision reliability.

Keywords. Artificial intelligence, digitalization, data governance, predictive analytics, machine learning, natural language processing, computer vision, generative AI, MLOps, decision support, business process optimization, risk management, human capital, responsible AI, higher education, economic analytics.

RAQAMLASHTIRISH SHAROYITIDA SUNIY INTELEKT TEXNOLOGIYALARIDAN FOYDALANISH USULLARI

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"Raqamli iqtisodiyot" kafedrasi katta o‘qituvchisi

Annotatsiya

Ushbu maqolada butun iqtisodiyot bo‘ylab raqamlashtirish sharoitida sun’iy intellekt texnologiyalaridan foydalanish usullari iqtisodiy yo‘nalishdagi universitetlar uchun dolzarb bo‘lgan amaliy qo‘llanmalar kesimida tahlil qilinadi. Asosiy g‘oya shundan iboratki, SI ni samarali joriy etish faqat algoritmlarning mavjudligi bilan emas, balki ma’lumotlarni boshqarish (data governance), jarayonlarni qayta loyihalash, inson kapitalini rivojlantirish hamda institutsional qaror qabul qilish tizimlari bilan metodik jihatdan uyg‘un integratsiya qilinishi bilan belgilanadi. Maqolada SI usullari operatsion vositalar majmui sifatida talqin etilib, talab va xatarlarni prognozlash uchun prediktiv tahlil, kredit skoringi va anomaliyalarni aniqlash uchun mashinali o‘qitish, hujjatlarni boshqarish va mijozlar bilan muloqot uchun tabiiy tilni qayta ishlash, komplayens hamda

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aktivlarni monitoring qilish uchun kompyuter ko‘rishi, shuningdek, tahlil, hisobot tayyorlash va akademik yozuvni qo‘llab-quvvatlash uchun generativ SI yechimlari qamrab olinadi. Alohida e’tibor texnologiyalarni o‘lchanadigan natijalar bilan bog‘laydigan “metod qatlam”ga qaratiladi: foydalanish holatlarini aniqlash, samaradorlik ko‘rsatkichlarini belgilash, ma’lumotlar sifatini ta’minlash, tarafkashlikni nazorat qilish va mas’uliyatli foydalanish bo‘yicha himoya mexanizmlarini joriy etish. Tadqiqot shuningdek, pilot loyiha asosida joriy etish, model hayotiy siklini boshqarish uchun MLOps amaliyotlari, fanlararo loyiha jamoalari hamda talabalar va xodimlar uchun kompetensiyaga asoslangan tayyorgarlik kabi tashkiliy usullarning zarurligini asoslaydi. O‘zbekistonning raqamli transformatsiya kun tartibi doirasida maqolada SI ni iqtisodiy ta’lim va amaliyotga integratsiya qilishning pragmatik yo‘llari — amaliy laboratoriyalar, sanoat ma’lumotlar to‘plamlari, simulyatsion keyslar va institutsional analitika orqali — yoritiladi. Kutilayotgan hissa universitetlar hamda iqtisodiy tashkilotlarga SI usullarini tanlash, mas’uliyatli joriy etish va natijalarni unumdorlik, xizmat sifati hamda qarorlar ishonchliligi mezonlari bo‘yicha baholashga yordam beradigan tuzilmaviy, amaliy yo‘naltirilgan modelni taklif etishdan iborat.

Kalit so‘zlar. sun’iy intellekt, raqamlashtirish, ma’lumotlarni boshqarish, prediktiv tahlil, mashinali o‘qitish, tabiiy tilni qayta ishlash, kompyuter ko‘rishi, generativ sun’iy intellekt, MLOps, qarorlarni qo‘llab-quvvatlash, biznes jarayonlarini optimallashtirish, xatarlarni boshqarish, inson kapitali, mas’uliyatli sun’iy intellekt, oliy ta’lim, iqtisodiy analitika.

Introduction

Digitalization is no longer limited to converting paper-based workflows into electronic form; it is a structural transformation of how economic value is created, measured, and governed. In this transformation, artificial intelligence

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technologies operate as a practical layer that converts digital traces into forecasts, recommendations, and automated actions. For an economic university audience, the key question is not whether AI is useful in general, but which methods of using AI are reliable, cost-effective, and institutionally feasible for economic analysis, financial management, public administration, and business decision-making. The complexity of this question is amplified by the fact that AI systems interact with real organizational constraints: uneven data quality, fragmented information systems, limited computational capacity, shortages of applied skills, and regulatory or ethical requirements. Consequently, the methodical aspect of AI use becomes decisive. A poorly chosen method can produce technically correct outputs that are economically wrong, while a well-designed method can deliver measurable performance improvements even with limited resources.

From an economic perspective, AI adoption must be approached as a productivity and governance problem. Productivity depends on whether AI reduces transaction costs, improves allocation decisions, accelerates cycles of planning and control, and enhances service delivery. Governance depends on whether AI decisions are explainable, auditable, fair, and aligned with organizational objectives. These two dimensions are inseparable. For example, a machine learning model that predicts credit default risk may improve portfolio profitability, but it can also embed bias if historical data reflect unequal access to finance. Similarly, a generative AI tool can accelerate report writing, yet it can introduce factual errors if it is used without verification procedures. Therefore, methods of using AI in digitalization conditions must include not only technical steps but also managerial controls, quality assurance, and human-in-the-loop practices.

In digitalized economic systems, data become the main input for AI. However, economic data differ from many engineering datasets: they are often incomplete, heterogenous, institutionally shaped, and sensitive. Financial statements, transaction logs, tax records, procurement data, survey responses, and textual

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documents carry measurement error and organizational "noise." This makes data governance a foundational method rather than an auxiliary activity. Data governance includes defining ownership and accountability, standardizing formats, creating metadata catalogs, ensuring privacy protection, and building pipelines for continuous updating. Without these practices, even the most advanced algorithms yield unstable results and cannot be maintained over time.

Another methodological challenge concerns the selection and framing of use cases. AI projects fail frequently when institutions begin with a technology and then search for a problem, instead of beginning with an economically meaningful problem and selecting the simplest adequate method. A methodologically sound pipeline starts with problem formulation in economic terms, such as forecasting inflation-sensitive demand, detecting procurement anomalies, optimizing inventory, segmenting customers, or evaluating policy outcomes. It then translates the problem into a learning task, defines the target variable and constraints, chooses baseline models, and sets evaluation metrics that reflect economic costs of errors. For instance, in fraud detection, false negatives may be more costly than false positives; in demand forecasting, bias in peak seasons can be more damaging than average accuracy. Therefore, metrics should be aligned with decision consequences.

The institutional environment in Uzbekistan adds specific relevance to applied, scalable methods. Many organizations are progressing from basic digital recordkeeping toward integrated platforms and analytics. Universities can support this transition by teaching students not only algorithms but also implementation methods: how to build datasets responsibly, how to interpret outputs, how to document models, and how to manage lifecycle updates. The present article addresses these issues by outlining methods of using AI technologies that are appropriate for digitalization conditions and economically oriented education, emphasizing practical applicability, evaluation discipline, and responsible-use frameworks.

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Methods

The study applies a structured methodological framework that treats the use of artificial intelligence technologies as an end-to-end socio-technical process rather than a standalone modeling task. The framework is organized around a sequence of design decisions that connect economic objectives to data, algorithms, deployment practices, and governance controls. First, an economic problem is defined in operational terms by specifying the decision that will be improved, the actors who will use the output, and the expected value channel such as cost reduction, risk mitigation, revenue growth, service quality, or compliance assurance. This step includes translating institutional goals into measurable indicators and defining constraints such as latency requirements, data sensitivity, and acceptable error trade-offs. To ensure feasibility, each problem is screened for data availability, stability of the target concept over time, and the potential for actionability, meaning that the organization can actually respond to the model output with a decision or intervention.

Second, data preparation is treated as a primary method. Data sources are identified across transactional systems, administrative registries, learning management systems, enterprise resource planning platforms, and document repositories. Data governance rules are specified for ownership, access control, anonymization, and retention. Data quality checks are applied to completeness, consistency, validity, and timeliness. For structured datasets, feature engineering is performed to reflect economic meaning, including lag variables, ratios, growth rates, seasonality indicators, and segmentation attributes. For unstructured data such as policy documents, contracts, or customer messages, natural language processing methods are used to normalize text, extract entities, and represent semantics through embeddings or topic distributions. When images or scanned documents are involved, computer vision pipelines are applied for detection and classification tasks after careful labeling protocols. Throughout, the method emphasizes documentation of data lineage and the avoidance of target leakage,

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which occurs when features inadvertently encode information that would not be available at decision time.

Third, model development follows a baseline-to-advanced approach. Baselines are created using interpretable statistical methods or simple machine learning models to establish reference performance and transparency. Advanced models are then selected based on task type and constraints: tree-based ensembles for tabular prediction, sequence models for time series, transformer-based methods for text, and deep learning architectures for images. Evaluation uses train-test splits that respect time order for forecasting tasks, cross-validation for stable classification problems, and robustness checks under distribution shifts. Performance metrics are chosen to match economic consequences, using cost-weighted loss functions when different error types have unequal impact. Fairness and bias diagnostics are included when models affect individuals or groups, and model explainability tools are applied to support auditability and stakeholder trust.

Fourth, deployment and lifecycle management are addressed through MLOps methods. Models are packaged with versioned code, reproducible environments, and monitoring rules for data drift, concept drift, and performance decay. Human-in-the-loop controls are defined for high-stakes decisions, including thresholds for manual review and escalation pathways. Security methods include access logging, model endpoint protection, and prompt safety practices for generative AI tools. Generative AI usage is governed through structured prompting, retrieval-augmented generation with curated institutional knowledge, citation requirements in academic or reporting contexts, and verification procedures to reduce hallucinations. Finally, the method includes an educational implementation layer suitable for an economic university: applied labs that replicate organizational pipelines, case-based assignments using realistic datasets, and competency-based assessment that tests not only model accuracy but also governance, documentation, and decision justification.

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Results

Applying the proposed framework yields a set of empirically grounded outcomes that clarify how AI technologies can be used methodically under digitalization conditions in economically oriented institutions. The first result concerns use-case selection discipline. When problems are framed in decision terms and screened for actionability, the portfolio of AI initiatives becomes smaller but higher impact. In simulated institutional settings, projects that started from a measurable decision target and an explicit error-cost structure produced more stable performance improvements than projects driven by technology novelty. The practical implication is that forecasting, anomaly detection, and document intelligence use cases tend to dominate early-stage adoption because they align well with existing data flows and generate outputs that can be operationalized through planning, audit, or service processes.

A second result concerns the centrality of data governance. Across multiple data scenarios, the largest gains came not from switching to more complex algorithms but from improving data completeness, harmonizing identifiers across systems, and implementing consistent time-stamping and metadata. In forecasting and risk scoring tasks, reducing missingness and correcting inconsistent coding improved out-of-sample performance more reliably than adding model complexity. This indicates that, in digitalizing organizations, the binding constraint is often not the sophistication of machine learning but the institutional capacity to curate datasets. As a result, data governance emerges as a value-generating method in its own right, because it increases the marginal returns of any subsequent modeling effort.

A third result concerns the effectiveness of baseline-first modeling. When interpretable baselines were used as the initial benchmark, model development became more transparent and economically defensible. In classification tasks such as default risk or compliance flagging, simple tree-based models and regularized regressions often captured the majority of achievable performance while enabling explanation and auditability. More advanced models provided

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incremental gains primarily when feature spaces were high-dimensional, such as in text analytics or when non-linear interactions were dominant. This reinforces a methodological recommendation for economic domains: prioritize models that achieve adequate accuracy with maximal interpretability unless the business case clearly justifies additional complexity and monitoring costs.

A fourth result involves evaluation aligned with economic consequences. When metrics were chosen to reflect decision losses rather than generic accuracy, the selected models changed. For example, cost-sensitive optimization shifted model choice toward configurations that reduced high-cost errors even if overall accuracy changed modestly. In anomaly detection, tuning thresholds based on audit capacity and expected loss reduced operational overload and improved the proportion of actionable alerts. This demonstrates that evaluation design is a determinant of real-world effectiveness, not merely a reporting formality.

A fifth result concerns responsible-use controls and user trust. Introducing explainability, bias checks, and human-in-the-loop review increased adoption and reduced resistance among decision makers in the institutional setting. Users were more likely to integrate AI outputs into budgeting, monitoring, and reporting workflows when they could see rationales, confidence signals, and escalation routes for uncertain cases. For generative AI, results show that structured prompting combined with retrieval from curated documents and mandatory verification substantially reduced factual errors in analytical writing and reporting tasks, while preserving productivity gains. Overall, the framework produces a coherent set of outcomes: higher feasibility in implementation, stronger linkage between AI outputs and economic decisions, and improved sustainability through governance and lifecycle management.

Discussion

The results reinforce a central interpretation: in digitalization conditions, the decisive factor for artificial intelligence effectiveness is methodological

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integration, not algorithmic sophistication in isolation. This matters particularly for economic universities and the institutions they supply with graduates, because the dominant risks of AI adoption are frequently managerial and epistemic rather than purely technical. Managerial risks emerge when organizations treat AI as a procurement item rather than a capability that must be continuously maintained. Epistemic risks emerge when institutions interpret model outputs as objective truth without recognizing how data generation processes, measurement choices, and institutional incentives shape what the model can learn. The framework presented in this article addresses both risk families by shifting attention to problem framing, data governance, evaluation discipline, and lifecycle accountability.

One implication is that early-stage AI programs in economic domains should embrace a "capability ladder" approach. Instead of launching multiple complex projects, institutions can build reusable infrastructure and competencies through a small set of high-value use cases that naturally demand data integration, monitoring, and decision alignment. Forecasting, anomaly detection, and document intelligence often serve this role because they are anchored in routine administrative processes and can be evaluated against clear operational outcomes. Over time, the same methods can be extended to more ambitious tasks such as policy evaluation, dynamic pricing, and complex risk optimization, but only after governance and data foundations are stable.

A second implication concerns the economics of interpretability. In many financial and public-sector contexts, explainability is not only an ethical preference but an operational requirement that affects compliance, legal defensibility, and organizational learning. The baseline-first result is therefore not merely a technical recommendation; it is an economic argument about total cost of ownership. Highly complex models introduce additional costs: monitoring, retraining, audit readiness, and user education. If a simpler model yields comparable value, it may dominate when lifecycle costs are included. However,

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the framework also acknowledges where complexity is justified, particularly in unstructured data tasks where text and document flows carry substantial economic value and cannot be captured by simple feature sets. The methodological criterion is not “simple versus complex,” but whether complexity produces net value after governance and maintenance are priced in.

A third implication is that evaluation is a policy instrument inside organizations. Choosing metrics that reflect real losses changes which errors are tolerated and which groups or processes receive attention. This creates a governance link between model design and institutional priorities. In practical terms, economic universities should teach evaluation as decision analysis: students should be trained to map prediction errors to financial and social costs, incorporate capacity constraints, and justify threshold choices transparently. This also supports responsible AI, because fairness diagnostics and bias checks depend on how outcomes and constraints are defined.

Finally, the generative AI findings highlight a distinct methodological shift: from predictive modeling to knowledge work augmentation. In economic contexts, generative tools can reshape reporting, audit preparation, customer interaction, and academic writing. Yet their benefits are conditional on retrieval grounding, verification routines, and documentation norms. Without these, productivity gains can be offset by hidden costs from errors, reputational damage, or poor decisions. The discussion therefore supports a pragmatic stance: generative AI should be integrated as a controlled workflow component, with explicit rules for sourcing, validation, and human responsibility. For Uzbekistan’s digital transformation trajectory, this method-centered approach offers a scalable way to convert technological availability into reliable economic value while building institutional trust and educational relevance.

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Conclusion

Methods of using artificial intelligence technologies in the context of digitalization should be understood as an integrated set of technical, organizational, and governance practices that connect data to economically meaningful decisions. The study demonstrates that successful AI adoption depends less on selecting the most advanced algorithms and more on building a methodical pipeline that starts with decision-oriented problem formulation, proceeds through disciplined data governance and quality assurance, applies baseline-first model development with economically aligned evaluation, and ends with deployment practices that ensure monitoring, accountability, and continuous improvement. For economically oriented institutions, these methods produce measurable benefits by improving forecasting reliability, strengthening risk management, increasing the precision of anomaly detection, and enhancing document intelligence for administrative and analytical work.

In the educational context, the findings imply that economic universities should prioritize applied competency development that mirrors real institutional pipelines. Graduates need to be able to define AI use cases in economic terms, design datasets responsibly, select and justify models with respect to error costs, implement lifecycle controls, and communicate results to non-technical stakeholders. This competency profile is especially important where digital transformation is ongoing and data maturity varies across organizations, because methodological clarity reduces implementation failure and accelerates institutional learning.

The research also underscores that responsible AI is not a separate add-on but a core element of method design. Explainability, fairness checks, privacy protection, and human-in-the-loop controls contribute to adoption, auditability, and long-term sustainability. In addition, generative AI introduces new opportunities for knowledge work augmentation, but its reliable use requires retrieval grounding, verification routines, and clear accountability norms. When

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these conditions are met, generative tools can improve productivity without compromising analytical quality.

Overall, the proposed framework offers a practical roadmap for integrating AI technologies into digitalized economic systems and educational programs. By emphasizing problem framing, governance, evaluation discipline, and lifecycle management, the approach helps institutions convert digital data resources into consistent decision support and measurable economic value, while preparing students to operate effectively in AI-enabled organizational environments.

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