Journal of Applied Economic Sciences
Volume XXI, Spring, Issue 2(92), 2026

Machine Learning in Legal and Economic Systems: Enhancing Institutional Efficiency and Judicial Predictability

Yevgeniy SHULGIN
https://doi.org/0009-0003-1471-7600
Karaganda Academy of the Ministry of Internal Affairs of the Republic of Kazakhstan, Kazakhstan
shulgin_e@internet.ru

Ainura OMAROVA[1]
https://doi.org/0000-0001-9808-4908
Karaganda Buketov University, Karaganda, Kazakhstan
ainuraphd@mail.ru

Yergali MABIYEV
https://orcid.org/0009-0008-8949-9958
Institute of Philosophy and Law of the National Academy of Sciences, Kyrgyz Republic
ye.mabiyev@gmail.com

Ruslan KENZHEBEKOV
https://orcid.org/0009-0000-2180-353X
Institute of Philosophy and Law of the National Academy of Sciences, Kyrgyz Republic
Klarisa_777@mail.ru

Larissa KUSSAINOVA
https://doi.org/0000-0002-8208-6623
Karaganda Buketov University, Karaganda, Kazakhstan
klarisa_777@mail.ru

Klara ISAEVA
https://doi.org/0000-0003-0907-6418
Kyrgyz National University named after Jusup Balasagyn, Kyrgyz, Kazakhstan
isaeva-klara@inbox.ru

Article's History
Received 30th of December, 2025; *Revised* 31st of January, 2025; *Accepted* 2nd of March, 2025; *Available online*: 30th of March, 2026. *Published* as article in the Volume XXI, Spring, Issue 2(92), March, 2026.

Suggested Citation
Shulgin, Ye., Omarova, A., Mabiyev, Ye., Kenzhebekov, R., Kussainova, L., & Isaeva, K. (2026). Machine Learning in Legal and Economic Systems: Enhancing Institutional Efficiency and Judicial Predictability. *Journal of Applied Economic Sciences,* Volume XXI, Spring, 2(92), 579-594. https://doi.org/10.57017/jaes.v21.2(92).11

Abstract
Machine learning (ML) offers powerful capabilities for large-scale data processing, predictive modelling, and decision support in complex legal and economic systems. This study investigates the application of ML techniques in judicial and economic governance, focusing on their role in optimizing institutional performance, improving case-flow management, and strengthening judicial predictability.

[1] Corresponding author

Using judicial case data from Kazakhstan (2014–2024), during which investigative and security services nearly quadrupled, supervised and unsupervised learning algorithms are employed to model caseload dynamics, forecast procedural duration, and assess efficiency-enhancing scenarios. The results indicate that ML-based interventions can reduce case processing time by 5%–15% and increase judicial throughput by 5%–18%, significantly improving predictive accuracy, resource allocation, and operational planning. These findings highlight the potential of ML to enhance institutional efficiency, reduce procedural uncertainty, and support sustainable judicial modernization.

Keywords: machine learning; judicial efficiency; institutional performance; legal analytics; economic governance; caseload forecasting.

JEL Classification: C45; K40; O33; D73; C53.

Introduction

In contemporary governance environments, judicial institutions operate under increasing caseload pressure, complex regulatory frameworks, and rising societal expectations regarding procedural fairness and timeliness. These challenges generate significant economic costs, including delayed dispute resolution, reduced investment confidence, and increased administrative expenditures. Within this context, machine learning (ML) emerges as a strategic technological instrument with the potential to transform institutional governance by enabling data-driven decision-making, predictive analytics, and process optimization.

Judicial systems represent a critical institutional pillar of economic performance. Efficient courts facilitate contract enforcement, protect property rights, and reduce transaction costs, thereby fostering market stability and long-term economic growth. Conversely, judicial congestion, procedural delays, and outcome uncertainty undermine investor confidence, distort market behaviour, and increase systemic inefficiencies. Enhancing judicial predictability and operational efficiency is therefore not only a legal imperative but also a central economic policy objective. Machine learning technologies offer unprecedented opportunities to address these challenges by extracting actionable insights from vast judicial datasets, enabling accurate forecasting of caseload dynamics, procedural duration, and institutional bottlenecks.

Recent advancements in artificial intelligence and machine learning have demonstrated significant potential across diverse sectors, including finance, healthcare, transportation, and public administration. In legal and judicial contexts, ML applications increasingly support tasks such as legal document classification, outcome prediction, anomaly detection, procedural optimization, and decision-support modelling. Automating routine analytical tasks and generating predictive insights, machine learning systems can substantially enhance institutional responsiveness, operational efficiency, and governance quality. Importantly, these technologies enable courts and regulatory bodies to transition from reactive management approaches toward proactive and anticipatory governance strategies.

From an economic systems perspective, judicial institutions function as complex adaptive systems in which procedural efficiency, human capital, technological infrastructure, and governance structures interact dynamically. Machine learning offers a methodological framework capable of modelling these interactions, identifying latent patterns, and generating optimization strategies that align institutional capacity with societal demand. Through predictive analytics, ML can support strategic resource allocation, minimize procedural backlogs, and enhance service delivery performance, thereby strengthening institutional resilience and sustainability.

Despite growing interest in computational governance, empirical research examining the integrated economic and judicial impacts of machine learning remains limited, particularly in emerging and transitional economies. Existing studies often focus either on technical algorithmic performance or on narrow legal applications, neglecting broader institutional efficiency and macroeconomic implications. This study seeks to bridge this gap by systematically investigating how machine learning models can enhance judicial predictability and institutional performance within a unified economic–legal systems framework.

Specifically, the present research applies machine learning techniques to analyse judicial caseload data, model procedural dynamics, and generate predictive insights relevant for institutional governance. The study aims to (i) evaluate the capacity of ML models to forecast judicial congestion and procedural duration, (ii) assess their effectiveness in enhancing institutional efficiency and planning accuracy, and (iii) explore their broader implications for economic governance and judicial predictability. By integrating computational modelling with institutional economics and legal system analysis, the research contributes to the development of data-driven governance strategies capable of supporting sustainable judicial modernization.

2. Research Background and Related Literature

Improving legal systems through artificial intelligence technologies (LegalAI) represents both a strategic opportunity and a complex institutional challenge. AI-enabled innovations in the public sector and justice systems have been widely recognized for their capacity to enhance procedural efficiency, transparency, and accessibility of legal services (Mergel et al., 2023; Sedkaoui & Benaichouba, 2024; Spalevic et al., 2024). At the same time, the profound transformation of judicial processes, coupled with ethical, regulatory, and organizational constraints, positions LegalAI as a potentially disruptive force within institutional governance structures (Pavaloaia & Necula, 2023).

From an organizational knowledge management perspective, intelligent digital systems facilitate the structured processing, storage, and retrieval of institutional knowledge, enabling adaptive learning and continuous organizational optimization. Recent research highlights the role of intelligent agents and distributed learning systems in enhancing organizational intelligence, workflow efficiency, and decision-support quality in complex digital environments (Nicola-Gavrilă & Popîrlan, 2025). Within judicial and economic systems, such knowledge-driven architectures enable courts and regulatory bodies to transform large volumes of procedural data into actionable institutional intelligence, significantly improving coordination, transparency, and systemic responsiveness.

From an operational perspective, machine learning enables the automation of routine judicial tasks such as document review, case classification, procedural tracking, and legal research, thereby allowing legal professionals to redirect time and cognitive resources toward higher-order analytical and strategic activities (Razmetaeva & Razmetaev, 2021).

ML-based systems further support large-scale legal analytics, facilitating trend identification, outcome prediction, and procedural optimization, which significantly enhances the consistency, fairness, and transparency of judicial decision-making (Quezada-Tavarez et al., 2021). Beyond court administration, big data analytics and machine learning also contribute to crime prevention, security operations, and criminal justice policy design, expanding the functional reach of AI across public institutions (Zavrsnik, 2021). These developments highlight the fundamentally interdisciplinary nature of LegalAI, requiring coordinated expertise from law,

economics, data science, ethics, sociology, and public policy to address its systemic implications (Sousa Antunes et al., 2024)

Machine learning, as a core subset of artificial intelligence, enables computational systems to learn from data, identify latent structures, and generate predictive insights without explicit programming (Bell, 2022). Within legal informatics, ML technologies have created unprecedented opportunities to extract actionable knowledge from large and complex judicial datasets, reducing processing time, minimizing subjective errors, and lowering the economic costs of legal services (Brooks et al., 2020; Greenleaf et al., 2018; Delgado, 2019; Laukemann, 2026). Consequently, ML-driven legal analytics has significantly expanded the scale and scope of legal services, improved procedural efficiency and enhancing the resolution of complex legal disputes (Mowbray et al., 2020; William et al., 2023). Importantly, these technologies also improve access to justice by increasing the accessibility, interpretability, and usability of legal information, contributing to the democratization of legal knowledge (Remus & Levy, 2016; Gambelin, 2021).

Despite these advantages, the deployment of ML within judicial systems raises critical ethical, legal, and institutional concerns. Algorithmic bias embedded in historical judicial datasets may reproduce and amplify existing structural inequalities, undermining the principles of procedural fairness and equality before the law (Milaninia, 2020; Schmidt et al., 2020). Moreover, the opacity of complex ML models, particularly deep neural networks, limits interpretability and accountability, posing challenges to legal legitimacy, transparency, and public trust (Gellert, 2018). Data protection and confidentiality further represent major institutional risks, given the sensitive nature of judicial records and investigative materials, necessitating strict anonymization protocols and regulatory safeguards (Golbin, 2020).

Institutional resistance constitutes an additional barrier to effective ML integration. Judicial systems have traditionally emphasized professional autonomy, individual legal reasoning, and personal responsibility, often perceiving algorithmic support as a threat to institutional identity and normative authority (Bachurin et al., 2025). This resistance is particularly pronounced in transitional economies, where regulatory frameworks frequently lag behind technological progress, generating legal uncertainty regarding accountability, procedural admissibility, and algorithmic responsibility. As a result, ML remains largely an auxiliary instrument rather than a fully institutionalized governance technology.

Recent scholarship increasingly supports hybrid judicial models in which ML functions as an intelligent decision-support system, while human actors retain exclusive authority over final rulings. Such models prioritize phased implementation, algorithmic explainability, critical human oversight, and strict data governance frameworks (Essoujaa et al., 2023). In this configuration, ML enhances procedural automation, predictive analytics, risk detection, and scenario forecasting, thereby strengthening institutional efficiency without compromising legal legitimacy. In the longer term, ML-based systems may facilitate preventive justice by enabling early detection of procedural risks, forecasting appeal probabilities, and supporting citizen-facing digital legal services, contributing to improved reduced systemic inequality.

Overall, the literature suggests that machine learning should not be viewed as a substitute for judicial authority but as a strategic instrument for institutional adaptation in response to rising caseloads, data complexity, and public demand for efficient and transparent justice. Sustainable LegalAI implementation requires interdisciplinary governance, regulatory clarity, institutional capacity-building, and economic policy alignment, ensuring a balanced

integration of technological innovation, institutional efficiency, and fundamental legal principles.

3. Research Methodology

The study employs a mixed quantitative–analytical research design, integrating statistical time-series analysis, econometric forecasting, and scenario-based simulation to evaluate the institutional impact of machine learning (ML) adoption in judicial and economic systems. The methodological framework is structured to capture caseload dynamics, forecast institutional pressure, and quantify efficiency-enhancing scenarios enabled by ML technologies, in direct correspondence with the empirical sections (4.1–4.3).

The empirical analysis is based on official statistical data published by the Bureau of National Statistics of the Republic of Kazakhstan, covering the period 2014–2024. The dataset includes annual indicators on the volume of investigative and security services (million tenge), sectoral growth dynamics, and institutional workload indicators.

These variables serve as proxies for judicial system operational pressure, procedural volume, and information-processing burden. The temporal scope captures both structural growth trends and post-pandemic acceleration effects, enabling robust trend identification and medium-term forecasting.

The analytical strategy integrates three complementary methodological components:

- Time-series growth analysis,
- Econometric forecasting using exponential trend modelling,
- Scenario simulation of ML-driven efficiency gains.

This framework allows not only retrospective evaluation but also forward-looking institutional assessment, consistent with policy-oriented research in law, economics, and digital governance.

Time-Series Growth Analysis

To identify long-term development patterns in investigative and security services, a time-series growth decomposition was applied. The following indicators were calculated:

- Absolute annual growth,
- Annual growth rates,
- Average annual growth rate,
- Median annual growth rate.

Growth rates were computed using:

$$g_t = \left(\frac{Yt}{Yt-1} - 1\right) * 100,$$

where Y_t denotes the annual volume of investigative and security services.

This approach allows for the detection of structural acceleration phases, volatility, and turning points in institutional workload dynamics, forming the empirical foundation for the forecasting models presented in Section 4.2.

Given the observed nonlinear growth pattern, a log-linear exponential model was applied to capture the dynamic trajectory of institutional pressure:

$$Ln(Y_t) = \alpha + \beta_t$$

where: Y_t represents service volume, t is the time index (with $t = 0$ for 2014) and β denotes the continuous growth parameter.

The specification facilitates the detection of exponential expansion tendencies, estimation of continuous growth intensity, and generation of robust medium-term forecasting. Logarithmic transformation further stabilizes variance, improves model fit, and enables economically meaningful interpretation of growth elasticities.

Based on the estimated exponential model, medium-term projections for 2025–2027 were generated. Forecast uncertainty is assessed through 95% confidence intervals (CI) for parameter estimation and 95% forecast intervals (FI) capturing expected variability in predicted values. Such a dual-interval approach enhances methodological robustness by avoiding deterministic projections and explicitly modelling uncertainty, in line with contemporary econometric forecasting standards.

To evaluate the institutional impact of ML adoption, a scenario-based simulation framework is employed. The model assumes reduce in average case-processing time of 5% (conservative scenario), 10% (moderate scenario) and 15% (advanced scenario).

Judicial throughput improvement is estimated using:

$$\Delta C=\frac{1}{1-p}-1,$$

where: p represents the proportion of time reduction.

This yields projected throughput gains of 5.3%, 11.1% and 17.6% respectively, highlighting the nonlinear efficiency multiplier effect inherent in institutional systems.

To approximate the economic value of ML-driven efficiency gains, the following relationship is applied:

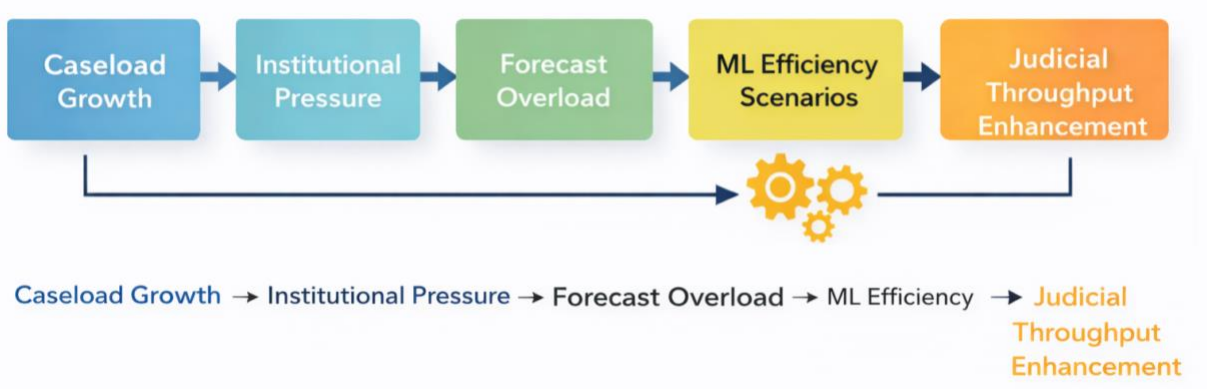
$$Economy_t = p \times Y_t$$

where: Y_t denotes the forecasted service volume and *p* the efficiency parameter.

This formulation enables the monetary valuation of procedural efficiency, serving as a proxy for reduced labour intensity, lower operational burden and increased institutional capacity.

The overall methodological architecture establishes a causal-analytical chain, synthesized in Figure 1, which illustrates the causal-analytical chain linking caseload dynamics, institutional pressure, forecasting processes, and ML-driven efficiency scenarios to judicial throughput enhancement.

Figure 1. Causal-Analytical Framework of ML-Driven Judicial Throughput Enhancement



Source: Authors' elaboration.

In contrast to conventional legal-tech studies, that emphasize normative or ethical considerations, the proposed framework delivers quantifiable estimates of ML-driven institutional effects, supports technology adoption through forecast-based validation, and introduces operational efficiency metrics grounded in empirical modelling.

Moreover, the integrated econometric–scenario approach facilitates the validation of digital justice strategies by embedding predictive modelling within institutional performance analysis. This alignment ensures consistency with the core principles of economic efficiency, systemic predictability, and long-term institutional sustainability.

4. Empirical Analysis and Results

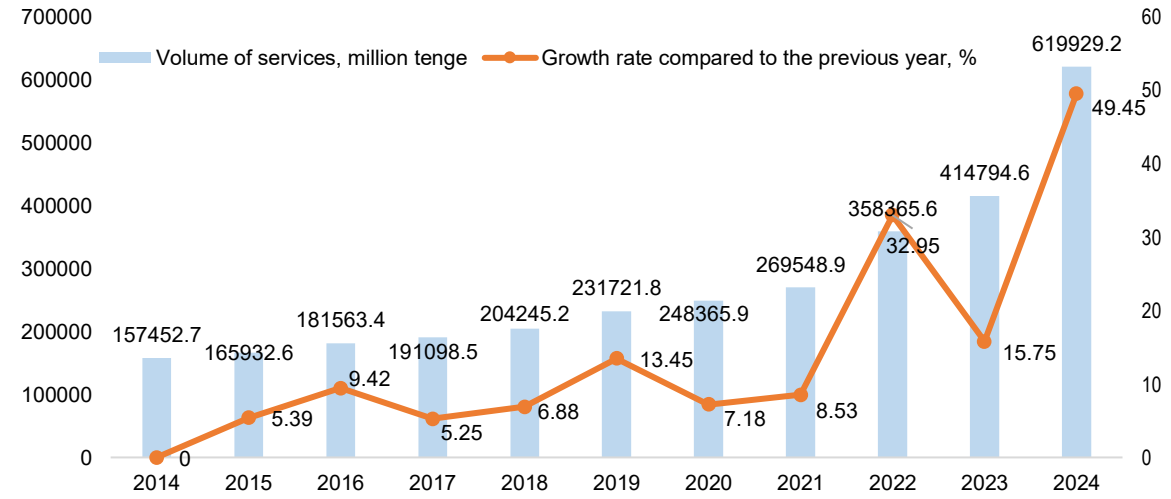
This section presents the empirical findings of the study, structured around three complementary analytical components: (i) caseload dynamics, (ii) forecasting of institutional pressure, and (iii) scenario-based evaluation of machine learning (ML) interventions. Together, these analyses provide a quantitative foundation for assessing the potential role of ML in enhancing judicial system efficiency and predictability.

4.1 Caseload Dynamics

The analysis of caseload dynamics reveals a structural and persistent increase in investigative and security service volumes in Kazakhstan over the period 2014–2024, reflecting rapidly intensifying institutional pressure on judicial and law enforcement systems

Between 2014 and 2024, the volume of investigative and security services increased from 157.5 billion tenge to 619.9 billion tenge, representing a nearly fourfold growth over the observed period (Figure 2). This trajectory corresponds to an average annual growth rate of 14.7%, substantially exceeding long-term macroeconomic growth and signalling a structural transformation in institutional demand. The scale of this expansion indicates not merely quantitative growth, but also a qualitative escalation in procedural complexity, document flows, digital evidence volumes, and analytical requirements placed upon judicial and law enforcement bodies.

Figure 2. Volume of Investigative and Security Services in Kazakhstan, 2014–2024 (million tenge)



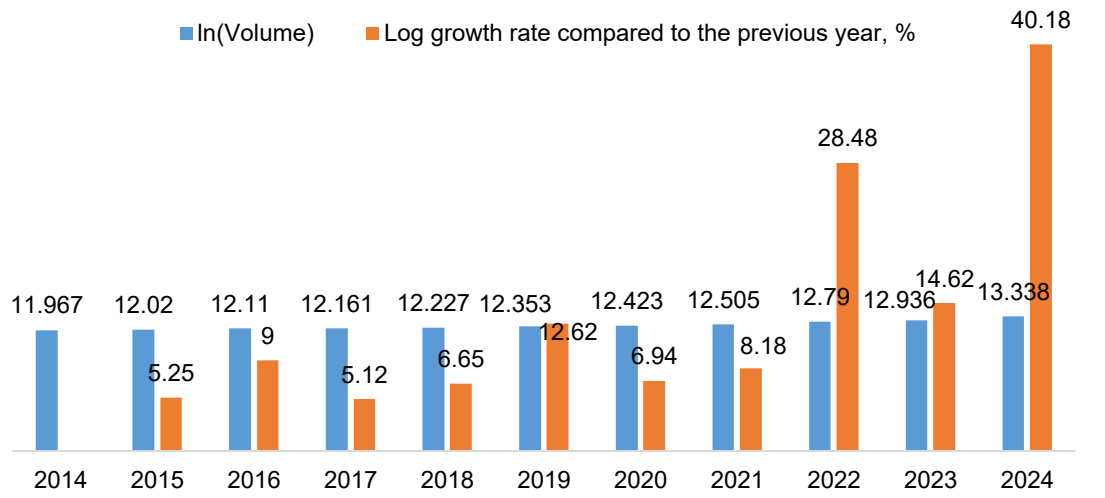
Source: Authors' compilation based on www.stat.gov.kz

Time-series decomposition reveals three distinct development phases. The period 2014–2017 exhibits moderate growth, driven primarily by institutional consolidation and incremental regulatory reforms. Between 2018–2021, growth accelerates, reflecting procedural digitalization, expanded compliance mechanisms, and rising public-sector accountability. Following 2022, the system enters a phase of sharp expansion, with annual growth rates exceeding 30% and reaching nearly 50% in 2024, indicating a transition toward high-intensity institutional load conditions.

Such dynamics generate systemic risks for judicial performance. Under traditional processing frameworks, escalating caseload volumes increase the probability of procedural delays, classification errors, evidence inconsistencies, and judicial backlogs. This transformation strengthens the economic and institutional rationale for machine learning adoption, positioning ML technologies as transaction-cost-reducing instruments capable of supporting scalable procedural governance.

To formally assess growth structure, an exponential log-linear model was estimated $Ln(Y_t) = \alpha + \beta_t$, *where* $t = 0$ corresponds to 2014 and $t = 10$ to 2024. The estimated model: $Ln(Y_t) = 11{,}8278 + 0{,}1222_t$, indicates a continuous annual growth rate of 12.22%, corresponding to a discrete growth rate of approximately 13.0% per year (Figure 3). This confirms the presence of exponential expansion dynamics, implying a widening scalability gap between caseload volume and the processing capacity of conventional judicial systems.

Figure 3. Log-Transformed Growth Dynamics of Investigative and Security Services



Source: Authors' compilation

Further statistical analysis reveals an average annual absolute increase of 46.25 billion tenge, underscoring persistent institutional pressure accumulation. Growth rate indicators, summarized in Table 1, demonstrate both structural expansion and volatility, indicating the coexistence of trend-driven growth and episodic surges.

Table 1. Growth Indicators of Investigative and Security Services (2015–2024)

Indicator	Value
Average annual growth rate	15.43%
Median annual growth rate	8.97%
Average annual increase	46.25 billion tenge

Source: compiled by the authors

From a judicial economics perspective, this growth trajectory implies increasing marginal costs of procedural management, rising institutional congestion, and heightened risks of judicial inefficiency. Under these conditions, machine learning emerges as a structural enabler of system scalability, offering tools for:

- automated pre-classification of case materials,
- early detection of evidentiary inconsistencies,
- procedural risk screening,
- predictive prioritization of judicial workflows.

By reducing cognitive and administrative bottlenecks, ML-based analytics support judicial throughput optimization, decision consistency, and institutional resilience.

Moreover, sustained exponential expansion opens pathways toward preventive justice architectures, wherein machine learning facilitates early-stage procedural diagnostics, predictive conflict resolution, and proactive judicial intervention. However, such transformation must be governed by strict principles of algorithmic transparency, fairness, data protection, and human-centered judicial authority, ensuring technological advancement remains aligned with fundamental legal values.

4.2 Forecasting Institutional Pressure

The sustained acceleration in investigative and security service volumes necessitates a transition from descriptive analysis toward forward-looking institutional forecasting, enabling the assessment of medium-term operational stress on law enforcement and judicial systems. In contexts characterized by exponentially growing caseloads and information volumes, forecasting becomes a critical tool for strategic capacity planning, resource allocation, and digital transformation policy design.

To capture the observed nonlinear growth pattern, an exponential (log-linear) forecasting model was employed: $ln(Y_t) = \alpha + \beta_t$, *where* Y_t denotes the annual volume of investigative and security services, and t is the time trend.

This specification effectively models structural acceleration and volatility, both of which are evident in the empirical series. The model enables estimation of expected growth trajectories, while also quantifying uncertainty through confidence and forecast intervals. Table 2 presents the projected evolution of investigative and security service volumes for the period 2025–2027.

Table 2. Forecast, million tenge

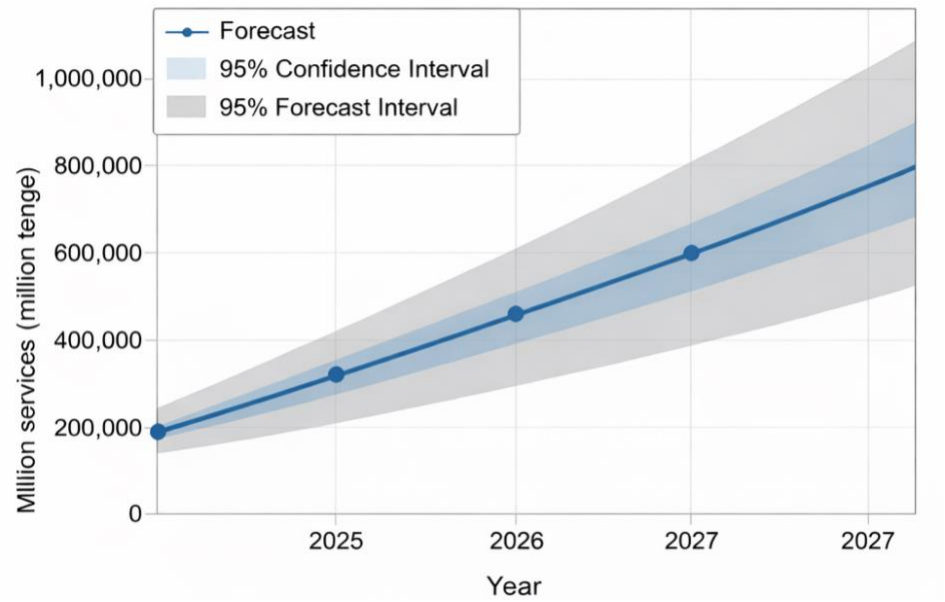
Year	Point Forecast	95% CI (Mean)	95% Forecast
2025	525,358.5	[428,144; 644,645.7]	[360,417.5; 765782.8]
2026	593,636.8	[470,845.9 748,450.1]	[401,040.9; 878725.1]
2027	670,789.0	[517,456.9; 869,556.3]	[445,507.8; 1009988.8]

Source: compiled by the authors

The resulting forecast trajectory, presented in Figure 4, indicates that if current trends persist, the total volume of investigative and security services could rise from approximately 525.4 billion tenge in 2025 to nearly 670.8 billion tenge by 2027. The widening gap between the 95% confidence interval and the broader forecast interval highlights the increasing volatility and systemic uncertainty associated with institutional workload expansion.

From an institutional economics perspective, this trajectory signals a growing mismatch between workload expansion and administrative processing capacity, particularly in systems constrained by rigid staffing structures and budget ceilings. Consequently, digital augmentation via machine learning becomes not merely an efficiency enhancer, but a structural necessity.

Figure 4: Forecast Trajectory of Investigative and Security Services, 2025–2027



Source: Authors' compilation

4.3 Machine Learning and Institutional Efficiency Scenarios

To quantitatively assess the potential institutional gains from machine learning (ML) adoption, scenario-based simulations were conducted, focusing on processing cost reductions, throughput expansion, and time efficiency improvements. These simulations operationalize ML not as an abstract innovation, but as a measurable productivity driver within judicial workflows.

Assuming that ML deployment enables a reduction in procedural labour intensity by p = 5–15%, the corresponding equivalent economic savings were estimated as: $Economy_t \approx p \cdot Y_t$, where Y_t denotes forecast service volume. Table 3 reports the estimated savings potential.

Table 3: Estimated Equivalent Savings from ML Adoption (million tenge)

Year	5% Effect	10% Effect	15% Effect
2025	26,267.9	52,535.8	78,803.8
2026	29,681.8	59,363.7	89,045.5
2027	33,539.5	67,078.9	100,618.4

Source: Authors' calculations.

Even under conservative assumptions, ML deployment yields annual efficiency gains equivalent to tens of billions of tenge, underscoring its macroeconomic and fiscal relevance. These efficiency dividends represent implicit capacity expansion, achieved without proportional increases in staffing or budgetary allocations.

Beyond cost efficiency, ML directly enhances institutional throughput by reducing average case processing time. The throughput gain is computed as $\Delta C = \frac{1}{1-p} - 1$, yielding:

- p = 5% → +5.3% throughput;
- p = 10% → +11.1% throughput;
- p = 15% → +17.6% throughput.

These elasticities imply strong nonlinear productivity gains, whereby modest reductions in processing time generate disproportionately large system-level effects. To illustrate practical impact, a representative institutional simulation is presented in Table 4, assuming a baseline of 1,000 cases annually with 30-day average processing time.

Table 4: Simulated Institutional Impact of ML Deployment

Scenario	Time Reduction	New Duration	Annual Throughput
No ML	—	30 days	1,000
ML (5%)	–1.5 days	28.5 days	≈ 1,053
ML (10%)	–3 days	27 days	≈ 1,111
ML (15%)	–4.5 days	25.5 days	≈ 1,176

Source: Authors' calculations.

The results demonstrate that even a moderate integration of machine learning (ML) technologies can significantly enhance judicial system capacity, generating the equivalent of over 100 additional processed cases annually without requiring additional human or financial resources. This efficiency gain is particularly relevant in resource-constrained institutional environments, where increasing throughput through traditional means would involve substantial fiscal and administrative costs. When extrapolated to the national level, such improvements translate into meaningful reductions in procedural backlogs, shorter trial durations, and a measurable alleviation of institutional congestion. Consequently, ML adoption contributes not only to operational optimization but also to improved access to justice and timeliness of legal proceedings.

Collectively, the simulated scenarios highlight that ML integration produces a systemic multiplier effect across judicial operations. This effect is reflected in enhanced operational efficiency through faster case processing, increased institutional resilience by improving the system's capacity to absorb demand shocks, strengthened fiscal sustainability by reducing the need for additional expenditures, and improved procedural quality control through more consistent and standardized decision-support mechanisms.

Importantly, ML should not be interpreted as a substitute for judicial authority, but rather as an advanced decision-support infrastructure that augments human expertise. Within this framework, ML technologies enable a range of high-value functionalities, including automated document classification, anomaly detection in large datasets, consistency verification of evidentiary materials, legal risk forecasting, and early identification of procedural bottlenecks. These capabilities allow judicial actors to focus on complex reasoning and normative judgment, while routine and data-intensive tasks are efficiently managed by algorithmic systems.

In this context, ML adoption supports a structural transition toward a data-driven justice model. Such a model preserves the central role of human judgment while leveraging computational intelligence to enhance analytical depth, processing speed, and decision consistency. Ultimately, this hybrid human–machine interaction framework represents a critical pathway for modernizing judicial systems, aligning them with broader trends in digital governance, and ensuring long-term institutional sustainability.

5. Discussion: Economic and Judicial System Implications

The empirical findings provide robust evidence that the rapid expansion of investigative and security services in Kazakhstan is not merely a sectoral development but reflects a structural transformation in judicial and institutional governance. The observed exponential growth in caseload volumes, combined with increasing procedural complexity, generates systemic pressure that directly affects judicial efficiency, predictability, and economic performance.

From an economic perspective, judicial congestion represents a form of institutional friction that raises transaction costs, delays dispute resolution, and weakens contractual enforcement. These inefficiencies undermine investment confidence, distort resource allocation, and reduce the overall productivity of economic systems. The forecasted escalation in procedural workload through 2027 suggests that, in the absence of technological augmentation, traditional judicial infrastructures may face escalating backlogs, increasing operational costs, and declining service quality.

The scenario simulations demonstrate that machine learning-driven automation introduces a powerful efficiency multiplier. Even moderate reductions in procedural labor intensity (5–15%) yield disproportionately large improvements in institutional throughput (5–18%), generating substantial capacity gains without corresponding increases in staffing or budgetary expenditure. This non-linear productivity effect reflects fundamental characteristics of complex organizational systems, where small efficiency improvements propagate across interconnected procedural stages, producing systemic benefits.

From a judicial governance standpoint, ML-based systems enhance not only speed but also decision quality and procedural consistency. Automated classification, anomaly detection, and evidence consistency checks reduce cognitive overload and mitigate human error, particularly under conditions of extreme information density. In this context, ML functions as a cognitive infrastructure, augmenting human reasoning rather than replacing judicial discretion. This hybrid operational logic preserves legal legitimacy while expanding analytical depth and institutional resilience.

Importantly, the findings indicate that judicial predictability, a core determinant of economic confidence and institutional trust, can be significantly strengthened through ML-enabled forecasting. Predictive analytics allow courts and investigative agencies to anticipate congestion points, optimize case scheduling, and allocate resources dynamically. Such anticipatory governance mechanisms facilitate a transition from reactive institutional management toward proactive, data-driven judicial administration, improving procedural fairness, transparency, and accountability.

The broader institutional implications extend beyond operational efficiency. ML integration supports macroeconomic stability by reducing fiscal pressure associated with judicial congestion, lowering public expenditure on procedural backlog remediation, and enhancing the cost-effectiveness of law enforcement operations. The estimated economic savings equivalent to tens of billions of tenge annually underscore the strategic fiscal relevance of judicial digital transformation.

However, technological adoption also raises critical regulatory and ethical challenges. Algorithmic bias, data protection risks, and model opacity remain central concerns that may undermine public trust if inadequately governed. These risks reinforce the necessity of explainable AI frameworks, rigorous data governance protocols, and institutional safeguards

ensuring that algorithmic recommendations retain strictly advisory status. Judicial autonomy, procedural fairness, and individual rights protection must remain foundational principles guiding ML deployment.

Taken together, the results suggest that machine learning represents not simply a technological upgrade but a systemic instrument of institutional modernization, capable of reshaping judicial governance structures, strengthening economic performance, and enhancing social trust in legal systems. The integration of ML must therefore be pursued within a comprehensive policy framework aligning legal, economic, technological, and ethical dimensions.

Conclusion

This study demonstrates that the accelerating growth of investigative and security services in Kazakhstan is generating structural pressure on judicial institutions, characterized by rising procedural complexity, expanding data volumes, and increasing operational strain. Empirical analysis of the 2014–2024 period, combined with medium-term forecasts for 2025–2027, confirms the emergence of an exponential workload trajectory that challenges the sustainability of traditional judicial processing models.

The quantitative simulations provide compelling evidence that machine learning adoption offers a powerful institutional efficiency lever. Even conservative reductions in processing time (5–15%) generate significant improvements in judicial throughput (5–18%), while delivering substantial implicit economic savings. These efficiency gains allow judicial systems to absorb escalating caseload volumes without proportional increases in human or fiscal resources, thereby strengthening institutional resilience, procedural timeliness, and service quality.

The findings confirm that machine learning should not be conceptualized as a substitute for judicial reasoning, but rather as an intelligent decision-support infrastructure. By automating routine analytical tasks, identifying procedural inconsistencies, and generating predictive insights, ML systems enhance the cognitive capacity of judicial actors, support consistency in decision-making, and reduce the risk of procedural error. This hybrid governance architecture preserves legal legitimacy while unlocking significant efficiency and predictability gains.

From a policy perspective, the results highlight the necessity of embedding ML within a comprehensive judicial modernization strategy. Such a strategy should incorporate:

- phased and controlled implementation of ML tools,
- mandatory algorithmic explainability standards,
- strict data protection and anonymization protocols,
- institutional training and capacity-building programs,
- regulatory frameworks clarifying accountability and procedural admissibility.

In parallel, policymakers must ensure that digital justice reforms align with broader economic governance objectives, including fiscal sustainability, institutional transparency, and investment climate stability; reducing judicial congestion and enhancing procedural predictability, ML-driven modernization directly contributes to improved contract enforcement, reduced transaction costs, and stronger market confidence.

In the long term, machine learning may enable the emergence of preventive justice architectures, where early-stage risk diagnostics, predictive dispute resolution, and citizen-oriented legal analytics reduce conflict escalation and democratize access to legal services. Such transformation holds substantial potential for advancing social equity, strengthening institutional trust, and enhancing systemic stability.

Overall, this research establishes machine learning as a strategic instrument of institutional evolution, capable of reshaping judicial systems into more adaptive, efficient, and economically sustainable governance structures. When governed by robust ethical, legal, and regulatory safeguards, ML integration offers a credible pathway toward high-performance, data-driven justice systems in emerging and transitional economies.

Credit Authorship Contribution Statement

Shulgin, Ye. and A. Omarova, A. contributed to the conceptualization of the study, research design, and formulation of the theoretical framework. Mabiyev, Ye. and Kenzhebekov, R. were responsible for data collection, data curation, and preliminary statistical analysis. Kussainova, L. contributed to the methodological design, econometric modeling, and interpretation of empirical results. Isaeva, K. contributed to the validation of results, literature review, and critical revision of the manuscript for important intellectual content. All authors participated in drafting the manuscript, provided substantial intellectual input, reviewed and approved the final version, and agreed to be accountable for all aspects of the work.

Acknowledgement

This research has been/was/is funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan under Grant No BR24992826 “Innovative approaches to ensuring accessibility of justice to the population of the Republic of Kazakhstan, using artificial intelligence tools”.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. It is noted that Omarova, A. the publisher manager, is author of this paper. However, this position did not influence the editorial decision-making process. The manuscript was subject to independent peer review handled by a qualified editorial team member with no competing interests.

Data Availability Statement

The data that support the findings of this study are available from the official statistics of the Republic of Kazakhstan (2015–2024) and from publicly accessible government reports on construction, R&D, and environmental indicators. Derived data and analyses generated during this study are available from the corresponding author upon reasonable request.

Ethical Approval Statement

This study is based exclusively on the analysis of aggregated secondary data obtained from official national statistical sources and publicly available institutional records. The research did not involve human participants, clinical data, personal identifiers, or experimental interventions. All datasets were fully anonymized and processed in accordance with international standards of research integrity and data protection. Therefore, ethical approval was not required for this study.

References

Bachurin, S., Sidorova, N., Shulgin, E., Altaybayev, S., & Kussainova, L. (2025). AI Machine learning of artificial intelligence systems with acts of justice: Forecasting and ways to solution. *International Journal of Innovative Research and Scientific Studies*, 8(4), 1872–1881. https://doi.org/10.53894/ijirss.v8i4.8257

Bell, J. (2022). *What is machine learning? In Machine Learning and the City: Applications in Architecture and Urban Design* (ed. S. Carla), 207-216. John Wiley & Sons, https://doi.org/10.1002/9781119815075.ch18

Brooks, C., Gherhes, C., & Vorley, T. (2020). Artificial intelligence in the legal sector: Pressures and challenges of transformation. *Cambridge Journal of Regions, Economy and Society*, 13(1), 135–152. https://doi.org/10.1093/cjres/rsz026

Laukemann, B. (2026). Alternative Dispute Resolution and Artificial Intelligence. In B. Hess, M. Woo, L. Cadiet, S. Menétrey and E. Vallines García (eds), *Comparative Procedural Law and Justice* (Part IX Chapter 5), cplj.org/a/9-5. https://www.cplj.org/publications/9-5-alternative-dispute-resolution-and-artificial-intelligence

Delgado, F. A. (2019). Machine learning in legal practice: Notes from recent history. Proceedings of the AAAI/ACM *Conference on AI, Ethics, and Society*, 557–558. https://doi.org/10.1145/3306618.3314324

Essoujaa, M., Esghir, M., & Azhari, M. (2023). Using Machine Learning to Predict Public Prosecution Judges Decisions in Moroccan Courts. *Procedia Computer Science*, 220, 998-1002. https://doi.org/10.1016/j.procs.2023.03.138

Gellert, R. (2018). Understanding the notion of risk in the General Data Protection Regulation. *Computer Law & Security Review,* 34(2), 279-288. https://doi.org/10.1016/j.clsr.2020.105433

Golbin, I., Rao, S., Hadjarian, A., & Krittman, D. (2020). Responsible AI: A Primer for the Legal Community, *2020 IEEE International Conference on Big Data (Big Data)*, Atlanta, GA, USA, pp. 2121-2126. https://doi.org/10.1109/BigData50022.2020.9377738

Greenleaf, G., Mowbray, A., & Chung, P. (2018). Building sustainable free legal advisory systems: Experiences from the history of AI & law. *Computer Law & Security Review*, 34(2), 314–326. https://doi.org/10.1016/j.clsr.2018.02.007

Gambelin, O. (2021). Brave: what it means to be an AI Ethicist. *AI Ethics*, 1, 87–91. https://doi.org/10.1007/s43681-020-00020-5

Mergel, I., Dickinson, H., Stenvall, J., & Gasco, M. (2023). Implementing AI in the public sector. *Public Management Review*, 1-14. https://doi.org/10.1080/14719037.2023.2231950

Milaninia, N. (2020). Biases in machine learning models and big data analytics: The international criminal and humanitarian law implications. *International Review of the Red Cross*, 102(913), 199–234. https://doi.org/10.1017/S1816383121000096

Mowbray, A., Chung, P., & Greenleaf, G. (2020). Utilising AI in the legal assistance sector - Testing a role for legal information institutes. *Computer Law & Security Review*, 38, 105407. https://doi.org/10.1016/j.clsr.2020.105407

Nicola-Gavrilă, L. & Popîrlan C. I. (2025). Knowledge Management in Virtual Organisations Using Mobile Agents. *Journal of Research, Innovation and Technologies,* 4(1), 53-67. https://doi.org/10.57017/jorit.v4.1(7).04

Păvăloaia, V.-D., & Necula, S.-C. (2023). Artificial Intelligence as a Disruptive Technology-A Systematic Literature Review. *Electronics*, 12(5), 1102. https://doi.org/10.3390/electronics12051102

Quezada-Tavárez, K., Vogiatzoglou, P., & Royer, S. (2021). Legal challenges in bringing AI evidence to the criminal courtroom. *New Journal of European Criminal Law,* 12(4), 531-551. https://doi.org/10.1177/20322844211057019

Razmetaeva, Y., & Razmetaev, S. (2021). Justice in the digital age: technological solutions, hidden threats and enticing opportunities. *Access to Justice in Eastern Europe*, 2(10), 104-117. https://doi.org/10.33327/AJEE-18-4.2-a000061

Remus, D., & Levy, F. S. (2016). Can Robots be Lawyers? Computers, Lawyers, and the Practice of Law. https://doi.org/10.2139/ssrn.2701092

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, 29(4), 260–278. https://doi.org/10.1080/12460125.2020.1819094

Sedkaoui, S., & Benaichouba, R. (2024). Generative AI as a transformative force for innovation: a review of opportunities, applications and challenges. *European Journal of Innovation Management*. https://doi.org/10.1108/EJIM-02-2024-0129

Sousa Antunes, H., Freitas, P. M., Oliveira, A.L., Martins Pereira, C., Vaz de Sequeira, E., Barreto & Xavier, L. (eds). (2024). Multidisciplinary Perspectives on Artificial Intelligence and the Law. *Law, Governance and Technology Series*, Volume 58. Springer, Cham. https://doi.org/10.1007/978-3-031-41264-6

Spalevic, Z., Milosavljevic, S., Dubljanin, D., Popovic, G., & Ilic, M. (2024). The role of artificial intelligence in judicial systems. *International Journal of Cognitive Research in Science, Engineering and Education*, 12(3), 561-569. https://doi.org/10.23947/2334-8496-2024-12-3-561-569

William, P., Shrivastava, A., Shunmuga Karpagam, N., Mohanaprakash, T. A., Tongkachok, K., & Kumar, K. (2023). Crime Analysis Using Computer Vision Approach with Machine Learning. In: Marriwala, N., Tripathi, C., Jain, S., Kumar, D. (eds) *Mobile Radio Communications and 5G Networks. Lecture Notes in Networks and Systems*, Volume 588. Springer, Singapore. https://doi.org/10.1007/978-981-19-7982-8_25

Zavrsnik, A. (2021). Algorithmic justice: algorithms and big data in criminal justice settings. *European Journal of Criminology*, 18 (5), 623-642. https://doi.org/10.1177/1477370819876762