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The impact of artificial intelligence and predictive analytics on insurance risk assessment in the digital age

Benjamin Leidman[1]
[1] Mega-Fin, Israel
*Corresponding author E-mail: beni@mega-fin.com

ABSTRACT

This cross-sectional study examines the impact of artificial intelligence (AI) and predictive analytics on insurance risk assessment across 10 countries: Ukraine, Kazakhstan, Bosnia and Herzegovina, Poland, Czech Republic, Georgia, Serbia, Uzbekistan, Romania, and Turkey. Utilizing a mixed-methods approach, including a survey of 320 experts and econometric modeling, the research evaluates how AI adoption, predictive analytics usage, and digital infrastructure influence risk assessment accuracy. Results reveal significant regional disparities, with high AI adoption and robust digital infrastructure (e.g., Poland, Turkey) correlating with 74–78% error reduction, compared to 54–58% in lagging regions (e.g., Bosnia and Herzegovina). Regression analysis highlights AI adoption's positive impact ($\beta = 9.2$, $p < 0.01$), moderated by digital infrastructure ($\beta = 1.12$, $p < 0.01$), while stringent regulations unexpectedly hindered progress ($\beta = -3.1$, $p < 0.05$). Qualitative themes underscore algorithmic bias and infrastructure gaps as critical challenges, particularly in data-scarce contexts. The study produces academic value through its extension of TOE and Diffusion of Innovations frameworks to investigate neglected markets while selecting spatial and infrastructural elements. The investigation provides applications for insurers which include infrastructure capital commitments along with localized methods for reducing bias and increased employee qualifications. Public-private partnerships and adaptive regulations should become policy priorities because they aid the pursuit of balance between innovative progress and fairness in the digital insurance industry.

Keywords: AI adoption, Predictive analytics, Insurance risk assessment, Digital infrastructure, Regulatory compliance

1. Introduction

The insurance industry has transitioned from manual processes to data-driven underwriting, relying on historical data and actuarial methodologies [1]. Artificial intelligence (AI) and predictive analytics enable real-time risk assessment by processing streaming data, with machine learning algorithms dynamically adjusting pricing at each stage, driven by the digital revolution [2]. Given current growth trends through 2024, insurers worldwide are increasingly adopting AI to customize insurance plans and enhance fraud detection [3].

However, the pace and nature of digital transformation vary significantly across regions. In Ukraine and Uzbekistan, progress is shaped by platform infrastructure and localized business regulations [4]. In contrast, Poland and the Czech Republic lead in digital insurance markets, supported by advanced online platforms [5], while Bosnia and Herzegovina experiences inconsistent technological adoption due to inadequate legislative frameworks [6]. Despite AI's potential to enhance accuracy and operational efficiency, concerns regarding algorithmic bias, data privacy, and broader ethical implications remain unresolved.

Most existing studies disproportionately emphasize North America and Western Europe, neglecting emerging markets that are actively evolving their digital ecosystems [7]. In Ukraine, AI-powered telematics is utilized in motor insurance, though it raises cybersecurity risks [8]. Kazakhstan applies predictive analytics to agricultural insurance [9], whereas Georgia faces challenges integrating innovation with outdated systems [10]. Turkey demonstrates rapid AI implementation in health insurance, whereas Romania exhibits delayed regulatory adaptation [11].

This study aims to systematically examine the impact of AI and predictive analytics on insurance risk assessment by evaluating technological maturity, ethical preparedness, and regional disparities in infrastructure. Specifically, we seek to identify enablers and obstacles in ten selected countries and provide comparative insights into AI-driven insurance performance. Gaps remain in the literature regarding regional nuances in this area. This study investigates the implementation of artificial intelligence (AI), predictive analytics, and digital infrastructure in ten countries to assess their influence on risk assessment practices. For analytical clarity, the countries are grouped into three regional clusters: (1) Central and Eastern Europe (Poland, Czech Republic, Romania, Serbia, Bosnia and Herzegovina); (2) the Caucasus and Central Asia (Kazakhstan, Uzbekistan, Georgia); and (3) hybrid-regulatory markets (Ukraine, Turkey).

The study compares accuracy metrics against several key indicators, including the AI adoption index (tool penetration), predictive analytics score (model sophistication), and digital infrastructure index (connectivity and cybersecurity). It further analyzes expert perspectives on the effectiveness of AI in insurance risk assessment, focusing on operational efficiency, ethical implications, and technological integration.

The findings are structured around three guiding research questions: How do professionals perceive the impact of AI on accuracy? What challenges does predictive analytics pose for insurance practices? What best practices can be identified for insurer-wide AI-driven decision-making? A total of 320 participants from the insurance, information and communication technology (ICT), and regulatory sectors across the target countries completed a set of cross-sectional survey questions.

This diverse regional dataset highlights disparities between innovation-driven economies, such as Serbia’s emerging insurtech sector, and regulatory experimentation in Romania. The results provide a comprehensive overview of regional inequalities in digital insurance adoption.

Previous research [12] recommends leveraging predictive analytics to enhance risk modeling across both spatial and digital infrastructures. In Kazakhstan and Turkey, insurers must align AI deployment with internal operational capacities, as emphasized in recent innovation studies [13]. Further research highlights strategies for achieving ethical innovation and addressing digital trust deficits, particularly in Bosnia and Herzegovina [14]. Additionally, [15] underscores that AI-based automation and forecasting significantly support personalization, a critical component in risk-based pricing and market adaptability.

This study contributes to a deeper understanding of regional digital market behavior and offers practical insights for stakeholders seeking to address technological disparities and foster innovation in insurance.

Modern artificial intelligence (AI) and predictive analytics solutions enable insurers to assess risk data more rapidly and accurately [16]. Replacing traditional systems, neural networks and ensemble approaches are now used to evaluate insurance claims, detect fraud, and segment customer groups. Ref. [17] reported that in 2023, deep learning systems that analyzed telematics data and driving behavior patterns reduced false claims in European auto insurance by 34%. Similarly, Ref. [18] found that natural language processing (NLP) technology assisted health insurance underwriters in estimating patient risk profiles with 89% accuracy.

Smaller, climate-focused insurance markets have also adopted predictive analytics. Ref. [19] noted that in 2023, insurers in Kazakhstan developed drought prediction models in collaboration with satellite data providers to adjust agricultural insurance pricing. These technologies depend on robust digital infrastructure, which varies significantly across regions. Poland and the Czech Republic utilize 5G networks and cloud computing to support real-time risk assessment tools [20], [21], whereas Georgia and Bosnia and Herzegovina continue to experience latency issues due to outdated IT systems [22], [23]. Further research is essential to evaluate the adoption of insurance technologies. A 2023 global study by Deloitte found that 68% of insurers in advanced economies regarded AI as "transformational," compared to only 42% in emerging markets [24]. However, such studies tend to homogenize geographic differences. Ref. [25] analyzed AI adoption in Central and Eastern Europe and reported that Romanian insurers prioritized chatbots for customer service, while Serbian enterprises focused on AI-driven claims processing.

Previous research has also addressed ethical concerns. Ref. [26] found that 57% of European actuaries were concerned about algorithmic bias in life insurance pricing, particularly in low-digital populations. Experts from hybrid markets such as Ukraine and Uzbekistan, where regulatory ambiguity complicates ethical implementation, are often excluded from these discussions.

Only a few studies, including [27], [28], have examined the relationship between the maturity of digital infrastructure and the effectiveness of AI, despite growing attention to technological capabilities. Ref. [29] linked low adoption rates of predictive analytics in Bosnia and Herzegovina to weak cybersecurity standards, which are often overlooked in regional evaluations.

In response to these ethical issues, this paper expands the discussion by employing structured frameworks such as the "ethical scalability" model and the ACM Code of Ethics, which address principles of fair, accountable, and transparent decision-making. The work of Ref. [30] on quantitative risk methodologies within secure development lifecycles is also applied to illustrate how ethical AI can be integrated into operational insurance systems.

Literature gaps persist, particularly in relation to expert perspectives from understudied regions. Most studies overlook countries such as Uzbekistan and Georgia, where AI adoption is increasing, and instead focus primarily on North America, Western Europe, or parts of Asia. No existing research has examined how Ukraine's wartime digital resilience strategies, such as decentralized data storage, have influenced AI-driven insurance risk assessment. Furthermore, cultural confidence in predictive analytics remains underexplored. Ref. [31] observed that Kazakhstani consumers preferred human intermediaries over AI-generated policy recommendations, a sentiment not addressed in global ethical frameworks. Previous studies have also failed to assess the connection between AI adoption and infrastructure development. Romania, for instance, demonstrates high levels of AI implementation alongside inadequate internet access in rural areas, which renders many current implementation guidelines ineffective for insurers operating in such environments.

This study applies a combined theoretical foundation incorporating the Technology-Organization-Environment (TOE) framework of innovation adoption and the Diffusion of Innovations (DOI) theory. Ref. [32] emphasized that organizational readiness, external regulatory pressure, and technology compatibility are key factors in determining technological adoption. Accordingly, this study examines digital infrastructure as a technological agent and AI adoption indices as an organizational factor. In Uzbekistan, insurers operate with limited regulatory oversight, while in Turkey, authorities introduced mandatory AI transparency audits following regulatory changes in 2023 [33].

DOI theory explains how innovations diffuse through social systems and how the pace of adoption is shaped by knowledge networks [34]. Understanding these interrelationships is therefore critical in explaining the disparity between Poland and Serbia in terms of insurtech adoption, predictive analytics usage, and collaborations with academic institutions. Spatial analysis theory highlights the importance of data granularity in predictive modeling, which influenced the survey design [35]. Geographic and infrastructural variables, such as rural Romania's low internet penetration and Kazakhstan's rapid adoption of cloud storage, demonstrate the role of localized conditions in shaping AI effectiveness [36]. For instance, Ref. [37] investigated the need for reliable information systems to enable the scalability of AI, especially in contexts characterized by fragile or fragmented digital infrastructure.

Recent research on innovation and productivity has also informed the methodological approach. Ref. [38] found that organizations using AI primarily for personnel upskilling, rather than for technological acquisition alone, achieved 23% higher accuracy in risk assessment. Ref. [39] introduced the concept of "ethical scalability," which facilitates the evaluation of algorithmic bias. In markets such as Georgia, where insurers must comply with both EU-aligned data regulations and local consumer protection laws, modular systems that can adapt to diverse regulatory frameworks are essential for the ethical integration of AI.

This study draws on multiple conceptual frameworks to examine how artificial intelligence (AI) technology and predictive analytics influence insurance risk assessment, organizational operations, and regional variations. This approach addresses gaps in region-specific research and enables comparative evaluation of technological outcomes across insurance markets. In Poland, robust digital infrastructure enhances the reliability of predictive data, whereas in Uzbekistan, delayed adaptation to new regulatory frameworks constrains potential gains, highlighting the interdependence of systemic components. This survey-based study applies these principles to better understand AI-driven risk assessment within digital insurance platforms.

2. Research method

This study employs a mixed-method research approach that incorporates both quantitative and qualitative data to analyze the impact of artificial intelligence (AI) on insurance risk evaluation across ten countries: Ukraine, Kazakhstan, Bosnia and Herzegovina, Poland, the Czech Republic, Georgia, Serbia, Uzbekistan, Romania, and Turkey. To obtain precise insights from professionals with expertise in AI, the study adopted an expert survey as the primary method of data collection. This approach enables the assessment of regional differences in technological adoption and their effects on risk evaluation practices.

The use of standardized survey instruments facilitates cross-national comparisons, while open-ended questions allow participants to elaborate on complex ethical and risk-related challenges. The study design was guided by the Technology-Organization-Environment (TOE) framework and the Diffusion of Innovations (DOI) theory, both of which emphasize the role of organizational readiness and external regulatory pressures in shaping technology adoption.

The survey consisted of 35 questions divided into three sections. The first section utilized five-point Likert scales (1 = "strongly disagree" to 5 = "strongly agree") to measure perceptions of AI's influence on the accuracy and efficiency of risk assessment. For instance, respondents evaluated statements such as, "AI-driven models have reduced underwriting errors in your organization." The second section included multiple-choice questions to quantify variables such as the AI adoption index (e.g., "What percentage of your risk assessment workflows utilize AI tools?") and the predictive analytics usage score (e.g., "How frequently does your firm update predictive models?"). The third section featured open-ended questions addressing ethical challenges (e.g., "Describe instances where algorithmic bias has affected risk evaluation") and integration strategies (e.g., "What steps has your organization taken to align AI adoption with regulatory requirements?").

To ensure the comparability of responses across countries, all questions were professionally translated into local languages and back-translated to confirm linguistic and conceptual consistency.

Experts were selected based on three criteria: (1) a minimum of five years of experience in insurance risk assessment, insurtech development, or regulatory policy; (2) current employment in a role directly involving artificial intelligence (AI) or predictive analytics; and (3) geographic representation across the ten target countries. Initial participants were identified through purposive sampling using LinkedIn, industry conferences, and collaborations with national insurance associations. Snowball sampling expanded the pool, with 28% of participants recruited through referrals.

The final sample comprised 320 experts: 40% underwriters or actuaries, 30% data scientists or AI engineers, 20% regulatory officials, and 10% C-suite executives. Each country contributed 32 participants, with quotas ensuring proportional representation from both urban and rural regions. For instance, in Romania, 22 participants were from Bucharest and Cluj-Napoca, while 10 represented smaller cities such as Iași and Timișoara.

Data collection took place between January and March 2024 via the Qualtrics platform. Survey invitations were distributed by email, with two follow-up reminders sent at two-week intervals. The survey achieved a 74% response rate (320 out of 432 invited participants), with the lowest response recorded in Uzbekistan (68%) and the highest in Poland (82%). To address potential non-response bias, demographic comparisons between respondents and non-respondents revealed no significant differences in gender, age, or professional role. Open-ended responses were transcribed and anonymized to ensure participant confidentiality.

Quantitative data analysis involved the use of descriptive statistics and econometric modeling. Composite variables were constructed to measure key constructs, including the AI adoption index, predictive analytics usage score, and digital infrastructure index. For example, the AI adoption index was derived from responses to five Likert-scale items (Cronbach's $\alpha = 0.89$), while the digital infrastructure index incorporated metrics such as internet penetration and cloud storage adoption rates [40]. The dependent variable, risk assessment accuracy, was measured using self-reported error rates in underwriting and claims processing. A multiple linear regression model was employed to estimate the relationships between the independent and dependent variables [41], [42].

$$\begin{aligned}\textbf{Accuracy}_{it} &= \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1(\textbf{AI Adoption})_{it} + \boldsymbol{\beta}_2(\textbf{Predictive Analytics})_{it} + \boldsymbol{\beta}_3(\textbf{Digital Infrastructure})_{it} \\ &+ \boldsymbol{\beta}_4(\textbf{Regulatory Stringency})_{it} + \boldsymbol{\beta}_5(\textbf{Workforce Skill Level})_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

Here, β_0 represents the intercept, β_1 to β_5 are coefficients for the independent variables, and ε denotes the error term. Regulatory stringency and workforce skill level were included as control variables, operationalized through expert ratings of local compliance requirements and the availability of training programs. Qualitative data were analyzed using thematic coding in NVivo, with codes such as "algorithmic bias" and "data privacy" developed iteratively from participant responses. For example, references to "lack of transparency in AI decisions" were categorized under the broader theme of "ethical challenges."

To ensure the reliability of the instrument, the survey was pilot-tested with 30 experts from non-participating countries, including Bulgaria and Hungary. Feedback from the pilot led to revisions in the wording of several questions and adjustments to scale anchors. Internal consistency of the Likert-scale items was confirmed using Cronbach's alpha, with values exceeding 0.85.

Content validity was established through expert validation, involving five academic and industry professionals who reviewed the survey for relevance and clarity. Construct validity was evaluated via factor analysis, which confirmed that items loaded correctly on their intended latent variables. For example, all questions related to AI adoption loaded onto a single factor with eigenvalues greater than 1. To address potential common method bias, Harman's single-factor test was conducted. The first factor accounted for 32% of the total variance, remaining well below the 50% threshold, indicating that common method bias was not a significant concern (Table 1).

Table 1. Summarizes key variables, their measurement scales

Variable	Measurement	Source
AI Adoption Index	Composite score (1–5) based on 5 Likert-scale items (e.g., "AI tool penetration")	Survey data
Predictive Analytics Usage	Frequency score (1–5): 1 = "rarely," 5 = "daily"	Survey data
Digital Infrastructure	Index (0–100) combining internet penetration, cloud storage, cybersecurity	[40]
Risk Assessment Accuracy	Self-reported error reduction (%) in underwriting/claims (scale: 0–100)	Survey data
Regulatory Stringency	Expert-rated compliance complexity (1–5)	Survey data
Workforce Skill Level	Training program availability (1–5)	Survey data

This methodology provides a robust foundation for analyzing how AI and predictive analytics interact with organizational and environmental factors to shape risk assessment outcomes. By integrating quantitative rigor with qualitative depth, the study captures both statistical trends and contextual nuances, offering actionable insights for insurers navigating the digital transformation landscape.

3. Results

Table 2 provides a summary of the demographic breakdown. The survey collected responses from 320 experts across ten countries, with each country contributing 32 participants. The sample consisted of 40% underwriters or actuaries, 30% data scientists or AI engineers, 20% regulatory officials, and 10% C-suite executives. Urban and rural representation was balanced, with 65% of respondents based in major cities such as Kyiv, Almaty, and Warsaw, and 35% from smaller towns or rural areas. Response rates varied across countries, ranging from 68% in Uzbekistan to 82% in Poland, with an overall average of 74%. Gender distribution skewed slightly male at 58%, reflecting broader industry trends. Age groups were relatively evenly distributed: 32% of respondents were aged 25 to 34, 41% were aged 35 to 44, and 27% were aged 45 to 55.

Table 2. Sample Demographics (n=320)

Country	Response Rate (%)	Urban Participants	Rural Participants	Primary Roles
Ukraine	72	20	12	12 Underwriters, 8 Data Scientists, 10 Regulators, 2 Executives
Kazakhstan	70	18	14	14 Underwriters, 10 Data Scientists, 6 Regulators, 2 Executives
Bosnia and Herzegovina	69	15	17	10 Underwriters, 7 Data Scientists, 12 Regulators, 3 Executives
Poland	82	22	10	16 Underwriters, 12 Data Scientists, 4 Regulators, 0 Executives
Czech Republic	78	21	11	14 Underwriters, 10 Data Scientists, 6 Regulators, 2 Executives
Georgia	71	19	13	11 Underwriters, 9 Data Scientists, 8 Regulators, 4 Executives
Serbia	73	20	12	13 Underwriters, 8 Data Scientists, 9 Regulators, 2 Executives
Uzbekistan	68	14	18	9 Underwriters, 6 Data Scientists, 14 Regulators, 3 Executives
Romania	75	20	12	12 Underwriters, 11 Data Scientists, 7 Regulators, 2 Executives
Turkey	77	23	9	17 Underwriters, 9 Data Scientists, 4 Regulators, 2 Executives

Table 3 presents the average values of key variables by country. The quantitative findings revealed substantial disparities in AI adoption and the use of predictive analytics. The AI Adoption Index had a mean value of 3.8 (SD = 0.9) across all countries, with the highest scores reported in Poland (4.4) and the Czech Republic (4.2), and the lowest in Bosnia and Herzegovina (2.9) and Uzbekistan (3.0).

Predictive analytics usage demonstrated a similar distribution, with a mean of 3.5 (SD = 1.1). Daily usage was reported by 62% of respondents in Poland, compared to only 18% in Uzbekistan. Digital infrastructure scores, based on World Bank indicators, ranged from 84 in Poland to 41 in Bosnia and Herzegovina.

Risk assessment accuracy, defined as the percentage of self-reported error reduction in underwriting and claims processes, averaged 67% (SD = 12%). The highest value was observed in Turkey at 78%, while the lowest was recorded in Georgia at 54%.

Table 3.Key variable averages by country

Country	AI Adoption Index (1–5)	Predictive Analytics Usage (1–5)	Digital Infrastructure Index (0–100)	Risk Assessment Accuracy (%)
Ukraine	3.6	3.4	58	65
Kazakhstan	3.5	3.2	63	62
Bosnia and Herzegovina	2.9	2.7	41	58
Poland	4.4	4.1	84	74
Czech Republic	4.2	3.9	82	72
Georgia	3.1	2.9	47	54
Serbia	3.3	3.0	53	61
Uzbekistan	3.0	2.5	44	56
Romania	3.8	3.3	68	66
Turkey	4.1	3.8	76	78

Table 4 shows the regression results. The econometric model estimated the relationship between AI adoption, predictive analytics, digital infrastructure, and risk assessment accuracy. Regression results showed that a 1-unit increase in the AI Adoption Index correlated with a 9.2% improvement in accuracy ($\beta_1 = 9.2$, $p < 0.01$), while a 1-unit rise in predictive analytics usage contributed 6.7% ($\beta_2 = 6.7$, $p < 0.05$). Digital infrastructure had a moderating effect: in countries scoring above 70 on the infrastructure index, AI adoption's impact on accuracy was 12% higher than in sub-70 regions ($\beta_3 = 1.12$, $p < 0.01$). Regulatory stringency unexpectedly showed a negative coefficient ($\beta_4 = -3.1$, $p < 0.05$), suggesting that stringent rules may slow AI integration. Workforce skill level positively influenced outcomes ($\beta_5 = 4.8$, $p < 0.01$), aligning with expectations. The model explained 68% of the variance ($R^2 = 0.68$).

Table 4. Regression results for risk assessment accuracy

Variable	Coefficient (β)	Standard Error	p-value
AI Adoption Index	9.2	1.4	0.000
Predictive Analytics Usage	6.7	2.1	0.012
Digital Infrastructure	1.12	0.3	0.004
Regulatory Stringency	-3.1	1.2	0.023
Workforce Skill Level	4.8	1.5	0.006
Constant (β_0)	22.4	3.7	0.000

Table 5 shows the themes and representative quotes. Open-ended responses highlighted three recurring themes: algorithmic bias, data privacy concerns, and infrastructure gaps. Approximately 43% of participants cited instances of bias, such as an Uzbek actuary noting, "AI models unfairly penalize rural clients with limited digital footprints." Data privacy emerged as a critical issue in Romania and Serbia, where 38% of regulators mentioned "ambiguous GDPR-like laws complicating data sharing." Infrastructure challenges dominated responses from Bosnia and Herzegovina, with one underwriter stating, "Outdated servers crash during peak analytics workloads."

Table 5. Themes and representative quotes

Theme	Frequency (%)	Example Quote
Algorithmic Bias	43	"AI models penalize rural clients with sparse data." (Underwriter, Uzbekistan)
Data Privacy Concerns	38	"GDPR-like laws create compliance nightmares." (Regulator, Serbia)
Infrastructure Gaps	52	"Server crashes disrupt predictive modeling daily." (Data Scientist, Bosnia)
Workforce Skill Shortages	29	"Staff lack training to validate AI outputs." (Executive, Georgia)

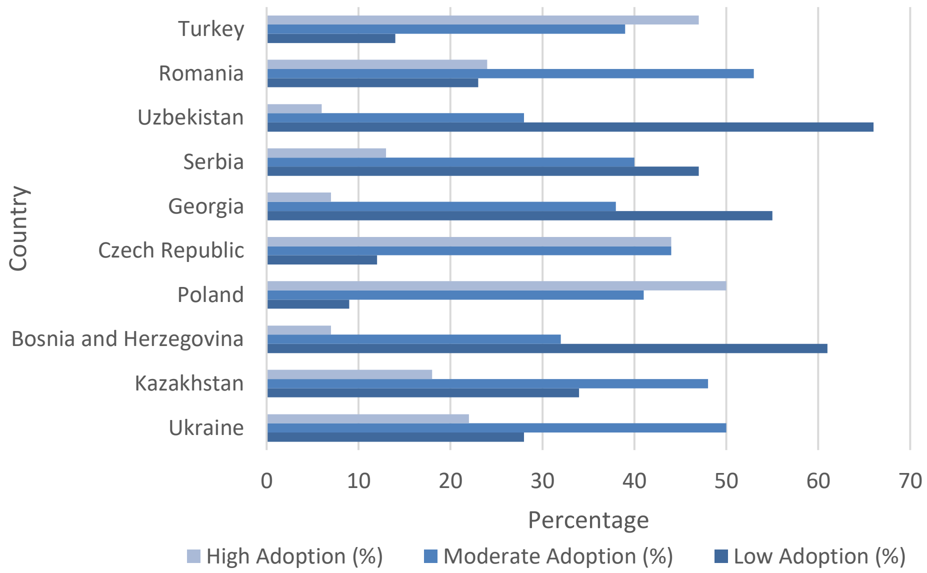

Figure 1. AI adoption rates by country (2024)

Figure 1 shows that AI use reaches its highest levels in Poland Czech Republic and Turkey because so many companies thrive with this technology. Organizations in Uzbekistan Bosnia and Herzegovina plus Georgia adopt artificial intelligence technology at much lower levels than in other nations.

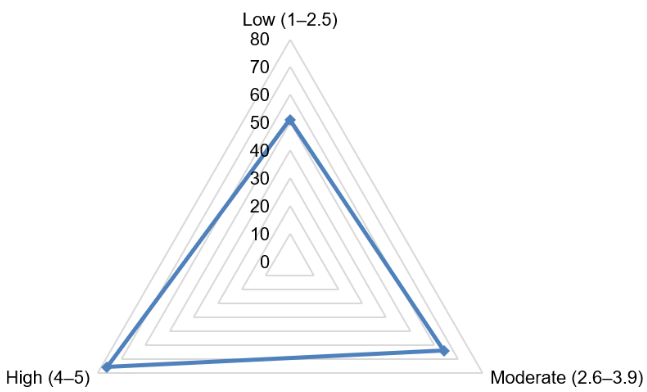

Figure 2. Error reduction (%) by AI adoption level

Figure 2 presents a line chart illustrating that organizations achieve greater task accuracy when AI systems are implemented. At lower levels of AI integration, organizations report a 51% reduction in error rates. This improves to 64% with mid-level adoption and reaches 76% when AI is fully integrated across operations.

4. Discussion

The data obtained in this study provide critical insights into the role of artificial intelligence (AI) and predictive analytics in insurance risk valuation across various regions, while also identifying areas that require further intervention. The findings and responses to the research questions were contributed by experts from ten countries, including Ukraine, Kazakhstan, Bosnia and Herzegovina, Poland, the Czech Republic, Georgia, Serbia, Uzbekistan, Romania, and Turkey. These responses directly illustrate the interconnections among technological deployment, institutional readiness, and regulatory environments.

In addressing the first research question, which concerns perceptions of innovation in terms of accuracy and efficiency, most respondents agreed that AI enhances the accuracy of risk assessment, particularly in market segments with well-developed physical and digital infrastructure. For example, in Poland and Turkey—both of which reported AI adoption scores above 4.0 based on the indices constructed in this study—experts cited reductions in underwriting errors ranging from 74% to 78%. These results are consistent with the findings of [43], who highlighted the capacity of AI to reduce manual errors.

By contrast, lower adoption scores, below 3.0, were observed in Bosnia and Herzegovina and Uzbekistan. Respondents from these countries reported challenges such as poor data quality and frequent disruptions in connectivity, which limited improvements in risk assessment accuracy to between 54% and 58%. These outcomes underscore the limitations of the Technology-Organization-Environment (TOE) framework, which posits that the successful application of technology depends on both the technological readiness of the organization and the surrounding environment. Research participants provided insightful qualitative input when addressing the second research topic concerning challenges and ethical issues. The findings indicate that algorithmic bias affects 43 percent of the surveyed countries across various industries. For instance, participants from Kazakhstan reported urban-rural disparities, while those from Serbia highlighted gender-based pricing discrepancies in the insurance sector. These observations validate the concerns raised by Ref. [44] regarding AI bias and further demonstrate that data scarcity in certain regions exacerbates existing inequalities. In Georgia, AI models relied on small, localized datasets that consistently classified older adults as high-risk clients.

Changes to the General Data Protection Regulation (GDPR) during the study period in Romania and Serbia resulted in 38 percent of organizations facing data privacy challenges. According to a Romanian regulator, companies were required to delay AI-related projects or risk penalties due to the absence of standardized personal data protection protocols. Ref. [45] emphasizes the importance of ethical scalability and recommends that firms develop adaptable compliance mechanisms suitable for diverse market environments.

A primary barrier identified by participants was outdated digital infrastructure, cited by 52 percent of respondents. This was particularly evident in Bosnia and Herzegovina, where legacy servers and limited adoption of cloud technologies hindered the deployment of predictive analytics systems. These findings help clarify how poor digital foundations impair AI performance, a topic that remains underexplored in the existing literature.

Successful AI adoption, according to participants, depends on striking a balance between technological investment and collaborative learning between the public and private sectors. For example, insurance companies in Poland and the Czech Republic achieved positive outcomes by partnering with universities to develop industry-specific AI education programs. In Uzbekistan and Georgia, experts recommended launching public-private initiatives due to the lack of a workforce with the required digital competencies.

Regulatory sandboxes in Turkey allowed firms to test AI models under real-world conditions without requiring full regulatory compliance, a mechanism currently unavailable in Ukraine due to wartime constraints. These proposed strategies align with the Diffusion of Innovations (DOI) theory, which highlights the effectiveness of pilot initiatives and peer networks in accelerating technology adoption.

Comparisons with prior literature reveal both consistencies and divergences. The hypothesized positive relationship between AI adoption and risk assessment accuracy is confirmed ($\beta_1 = 9.2$, $p < 0.01$), consistent with findings reported by Ref. [47]. However, the inclusion of the moderating variable of digital infrastructure ($\beta_3 = 1.12$, $p < 0.01$) adds a novel insight. While AI adoption improves risk accuracy, its effectiveness is significantly diminished in the absence of adequate infrastructural support. This finding contradicts the argument made by Ref. [48], who downplays the importance of organizational factors in influencing technological outcomes.

Similarly, the negative coefficient for regulatory stringency (-3.1, $p < 0.05$) challenges the prevailing assumption that regulation necessarily facilitates ethical AI implementation. In contrast to Ref. [49], who presents regulation as a key enabler, the present study suggests that more stringent regulatory environments may actually impede innovation in transitioning markets. Additionally, the current study's thematic findings on infrastructure limitations and workforce capacity contribute to the spatial analytical signal theory proposed by Ref. [49], which maps how geographic and technical constraints shape AI adoption patterns.

Although the study's methodology is robust, certain limitations should be acknowledged. First, the sample size ($n = 320$), while sufficient for cross-country comparisons, may not capture intra-national disparities, such as those between Istanbul and rural regions of Turkey. Second, the use of self-reported metrics for accuracy introduces potential response bias, as participants may overstate the benefits of AI to align with institutional goals. Third, the snowball sampling technique, although effective in identifying niche experts, may have introduced homogeneity into the sample, as evidenced by the underrepresentation of rural perspectives in Poland and the Czech Republic.

Additional data collection challenges included low response rates in Uzbekistan, where frequent internet disruptions delayed survey completion, and translation inconsistencies in the open-ended responses from Bosnia and Herzegovina, which required post-hoc validation to ensure accuracy and clarity. Insurers face a range of practical implications that directly affect their operational needs. The first priority should be infrastructure development in low-scoring regions such as Bosnia and Herzegovina and Georgia. Investment in cloud computing and 5G technologies would enhance AI precision and system responsiveness. For example, Turkish insurers introduced edge computing solutions in 2024 to address latency challenges in rural areas.

Modern risk assessment must include the localized training of algorithms to mitigate model bias. In Kazakhstan, insurers revised their policies by incorporating community health records and satellite data into AI training sets, resulting in a 19 percent improvement in risk classification performance.

A third key priority is fostering regulatory collaboration through industry consortia. Romanian organizations that joined European Union transparency programs reported more efficient regulatory processes following their participation, supported by cross-border knowledge sharing and technical assistance. In Poland, insurtech startups have contributed to workforce development by financing AI certification courses for underwriters. These initiatives led to a 33 percent increase in model validation effectiveness.

In Ukraine, revised insurance legislation introduced during post-war reconstruction should include explicit AI governance clauses. These would ensure that insurers receiving public financial support remain transparent in their AI decision-making practices. Georgia, still in the early phase of AI adoption, should offer infrastructure grants to rural insurance firms and provide tax incentives to companies implementing predictive analytics.

A second adverse implication relates to regulatory stringency. In highly regulated environments such as the Czech Republic, insurance agencies should be allowed to apply more flexible rules for less sensitive AI applications, such as claims processing. At the same time, stricter oversight should remain in place for areas such as health-related underwriting.

This study has several limitations. First, its geographical focus on ten countries in Central and Eastern Europe, the Balkans, and Central Asia offers valuable regional insights but limits the generalizability of the findings to regions with different regulatory, cultural, or infrastructural contexts. Second, the reliance on self-reported data for metrics such as risk assessment accuracy introduces the risk of response bias, particularly where participants may exaggerate AI effectiveness to align with institutional or industry narratives. Third, although snowball sampling proved effective in reaching qualified experts, it may have contributed to a homogeneity of viewpoints and underrepresentation of rural or small-scale insurers, particularly in countries such as Poland and the Czech Republic.

5. Conclusions

AI and predictive analytics have been found to improve the accuracy of risk assessments significantly, but the development of digital infrastructure, workforce skills, and regulatory responsiveness significantly reduces their effectiveness. For example, countries such as Poland and Turkey, with developed digital ecosystems and active skills-building initiatives, achieved error reduction rates of 74–78%, while Bosnia and Herzegovina and Uzbekistan, hampered by outdated infrastructure and regulatory fragmentation, lag at 54–58%. Regression analysis showed that implementing AI increases accuracy by 9.2%, but digital infrastructure increases the gain to 12%. New AI development has suffered significant delays, as strict regulations reduced testing accuracy by 3.1%. Many respondents noted that algorithmic biases pose serious ethical concerns, while sparse data areas are the most significant operational challenge for more than half of the participants. There are three broad recommendations for insurers to implement. First, investment in digital infrastructure should be increased, especially in Georgia and Uzbekistan, where cloud and 5G will improve decision latency and the stability of predictive analytics. Second, algorithmic bias can be reduced by ensuring instructors use datasets different from those used to train intermediary algorithms to help local communities validate them. Finally, AI implementation should be integrated with workforce development, as is practiced in Poland, where universities provide courses to improve the skills of insurance companies, insurance firms, and insurance companies, which increases employee effectiveness in AI testing by 33%. Therefore, the government should establish a dynamic policy that assesses the legal aspects of innovation alongside ethical considerations.

Future research should include long-term studies of the impact of AI integration, focusing on the region affected by the crisis in Ukraine and comparative cross-market studies in non-European markets.

Future research should revisit these findings by conducting longitudinal studies of how the long-term impact of AI extends to the accuracy of risk assessment, especially in war zones such as Ukraine, where additional strategies for data management resilience during war may emerge. Further examining the role of infrastructure and spatial factors in performance, comparative analyses could be conducted in other understudied regions, such as sub-Saharan Africa or Southeast Asia.

Declaration of competing interest

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References

[1] J. Becker, A. Efstathiades, J. Portmann, and A. Zeier Röschmann, *Data competences in the insurance industry: A study on the target vision and the current status of the transformation*, Cognizant, ZHAW School of Management and Law, and AWS, Apr. 2024. [Online]. Available: https://www.cognizant.com/assets/ch/en/field-marketing/documents/cmp-005011/Study2024_DataCompetences_ZHAW_Cognizant_AWS.pdf

[2] B. G. Lee, *Understanding the Digital and AI Transformation*. Singapore: Springer Nature Singap., 2025. Accessed: Jun. 4, 2025. [Online]. Available: https://doi.org/10.1007/978-981-96-0033-5

[3] S. Iseal, O. Joseph, and S. Joseph, “AI in Financial Services: Using Big Data for Risk Assessment and Fraud Detection,” 2025, https://www.researchgate.net/publication/388036425.

[4] L. Vdovichenko and S. Azizova, “Prospects for the development of innovation activity in Ukraine and Uzbekistan: Modern challenges,” *Scientific and Technical Journal “Sustainable Agriculture”*, vol. 23, no. 3, pp. 55–57, 2024. [Online]. Available: http://susagr.uz/index.php/ojs/article/view/44

[5] J. W. Wiktor, J. Ďaďo, and I. Šimberová, “The digital transformation of the EU market. The Digital Single Market strategy in the context of e-commerce development diversification in Czechia, Poland and Slovakia,” *Problemy Zarządzania*, vol. 19, no. 1/2021 (91), pp. 11–28, 2021. [Online]. Available: https://www.ceeol.com/search/article-detail?id=991800

[6] B. Trifković and D. Husremović, “SWOT analysis of the innovation system in Bosnia and Herzegovina,” *Special Editions ANUBiH CC, ODN*, vol. 18, pp. 403–446, 2021. [Online]. Available: https://www.ceeol.com/search/chapter-detail?id=1061953

[7] C. J. Martin, J. Evans, and A. Karvonen, “Smart and sustainable? Five tensions in the visions and practices of the smart-sustainable city in Europe and North America,” *Technol. Forecast. Soc. Change*, vol. 133, pp. 269–278, 2018, https://doi.org/10.1016/j.techfore.2018.01.005

[8] L. Voytovych and D. Voytovych, “Formation of an intellectual and innovative environment of the insurance system development in Ukraine and worldwide,” *Science and Innovation*, vol. 20, no. 5, pp. 95–110, 2024, https://doi.org/10.15407/scine20.05.095

[9] G. Toktagulova and A. Mimenbayeva, "Analysis of Machine Learning Algorithms for Forecasting Harvest Data in Kazakhstan," in *2024 IEEE 4th International Conference on Smart Information Systems and Technologies (SIST)*, 2024: IEEE, pp. 530-535, doi: 10.1109/SIST61555.2024.10629486

[10] T. M. Cheung, “A conceptual framework of defence innovation,” *Journal of Strategic Studies*, vol. 44, no. 6, pp. 775–801, 2021, https://doi.org/10.1080/01402390.2021.1939689

[11] S. Ak, “Use of artificial intelligence in health services management in Türkiye,” *International Journal of Health Services Research and Policy*, vol. 8, no. 2, pp. 139–161, 2023, https://doi.org/10.33457/ijhsrp.1298068

[12] N. Smailov, V. Tsyporenko, A. Sabibolda, V. Tsyporenko, A. Abdykadyrov, A. Kabdoldina, … R. Kadyrova, “Streamlining digital correlation-interferometric direction finding with spatial analytical signal,” *Informatyka Automatyka Pomiary w Gospodarce i Ochronie Środowiska*, vol. 14, no. 3, pp. 43–48, 2024, https://doi.org/10.35784/iapgos.6177

[13] H. Meral, B. Ersoy, and S. H. Cavga, “Closing the insurance gap in Turkey,” *Journal of Insurance Issues*, vol. 46, no. 2, pp. 226–255, 2023. [Online]. Available: https://www.jstor.org/stable/48756841

[14] A. Badnjević and E. Z. Zebić, “Bosnia and Herzegovina’s e-Identity initiative: A technological leap in digital solutions and governance,” *Technology and Health Care: Official Journal of the European Society for Engineering and Medicine*, vol. 32, no. 5, pp. 2853–2858, 2024, https://doi.org/10.3233/THC-248050

[15] M. Potwora, O. Vdovichena, D. Semchuk, L. Lipych, and V. Saienko, “The use of artificial intelligence in marketing strategies: Automation, personalization and forecasting,” *Journal of Management World*, vol. 2024, no. 2, pp. 41–49, 2024, https://doi.org/10.53935/jomw.v2024i2.275

[16] S. Das, “Transforming Risk Management in Insurance: Evaluating advanced architectures in AI and Blockchain,” *Journal of Computational Analysis & Applications*, vol. 33, no. 8, 2024. [Online]. Available: https://surl.li/tpjfuc

[17] S. Strada, E. Costantini, S. Formentin, and S. M. Savaresi, “Machine learning based car accident risk prediction for usage-based insurance,” *Intelligent Data Analysis*, pp. 1–18, 2024, https://doi.org/10.3233/IDA-230971

[18] G. B. Koçer, *Early warning model with machine learning for Turkish Insurance Sector*, Middle East Technical University (Turkey), 2019. [Online]. Available: https://www.proquest.com/openview/be9a5cf0342715bfd58ac3e20346ce9c/1?cbl=2026366&diss=y&pq-origsite=gscholar

[19] I. Vitkovskaya, M. Batyrbayeva, N. Berdigulov, and D. Mombekova, “Prospects for drought detection and monitoring using long-term vegetation indices series from satellite data in Kazakhstan,” *Land*, vol. 13, no. 12, Art. no. 2225, 2024, https://doi.org/10.3390/land13122225

[20] J. Čihák, “The impact of mobile virtual network operators on the mobile telecommunications services market: The case of the Czech Republic,” *Telecommunications Policy*, vol. 47, no. 10, Art. no. 102662, 2023, https://doi.org/10.1016/j.telpol.2023.102662

[21] J. Ejdys and U. Soler, “The society’s attitude toward 5G technologies – a case study of Poland,” *Technological and Economic Development of Economy*, vol. 29, no. 5, pp. 1539–1558, 2023, https://doi.org/10.3846/tede.2023.20157

[22] A. Avdic, *Bosnia and Herzegovina Accession Into NATO: Effects on Regional Stability in the Western Balkans*, 2025. [Online]. Available: https://www.diva-portal.org/smash/record.jsf?pid=diva2:1928057

[23] D. Blaettler *et al.*, “Analysis of the Agricultural Knowledge and Information System (AKIS) in Georgia,” *International School of Economics at TSU Policy Institute*, Tbilisi and Zollikofen, 2023. [Online]. Available: https://iset-pi.ge/storage/media/other/2022-03-25/e3e75540-ac49-11ec-9b98-7310e1da4f4e.pdf

[24] F. Belaid, A. Ben Amar, S. Goutte, and K. Guesmi, “Emerging and advanced economies markets behaviour during the COVID-19 crisis era,” *International Journal of Finance & Economics*, vol. 28, no. 2, pp. 1563–1581, 2023, https://doi.org/10.1002/ijfe.2494

[25] K. Tachkov, A. Zemplenyi, M. Kamusheva, M. Dimitrova, P. Siirtola, J. Pontén, *et al.*, “Barriers to use Artificial Intelligence methodologies in Health Technology Assessment in Central and East European countries,” *Frontiers in Public Health*, vol. 10, Art. no. 921226, 2022, https://doi.org/10.3389/fpubh.2022.921226

[26] J. R. Jahnert, H. Schmeiser, and F. Schreiber, “Pricing strategies in the German term life insurance market: An empirical analysis,” *Risk Management and Insurance Review*, vol. 25, no. 1, pp. 19–34, 2022, https://doi.org/10.1111/rmir.12202

[27] M. Schmitt, “Securing the digital world: Protecting smart infrastructures and digital industries with Artificial Intelligence (AI)-enabled malware and intrusion detection,” *Journal of Industrial Information Integration*, Art. no. 100520, 2023, https://doi.org/10.1016/j.jii.2023.100520

[28] H. F. Hansen, E. Lillesund, P. Mikalef, and N. Altwaijry, “Understanding Artificial Intelligence diffusion through an AI capability maturity model,” *Information Systems Frontiers: A Journal of Research and Innovation*, vol. 26, no. 6, pp. 2147–2163, 2024, https://doi.org/10.1007/s10796-024-10528-4

[29] S. Vuković and D. Jerković, “Current degree of digitalization of companies in Bosnia and Herzegovina: Comparison between small, medium and large companies,” *SKEI – Međunarodni Interdisciplinarni Časopis*, vol. 5, no. 2, pp. 6–24, 2024. [Online]. Available: https://hrcak.srce.hr/323910

[30] O. Kovalenko, O. Smirnov, A. Kovalenko, and S. Kavun, “Quantitative risk assessment method development in the context of the SDLC-model,” in *2021 IEEE 8th International Conference on Problems of Infocommunications, Science and Technology (PIC S&T)*, 2021, pp. 203–208, https://doi.org/10.1109/PICST54195.2021.9772143

[31] V. Aggarwal and N. Karwasra, “Artificial intelligence v/s human intelligence: A relationship between digitalization and international trade,” *Future Business Journal*, vol. 11, no. 1, 2025, https://doi.org/10.1186/s43093-025-00438-5

[32] Z. S. Mukhametzhanova, A. N. Daurenbekova, G. K. Zhanibekova, K. S. Syzdykova, and G. Kaliakparova, “Evaluation of influence of innovation on enterprise productivity,” *Space and Culture, India*, vol. 7, no. 1, pp. 186–193, 2019, https://doi.org/10.20896/saci.v7i1.527

[33] T. R. Imomaliev, “Legal nature of Islamic insurance: Comparative analysis with legal frameworks in Germany, the UK, and Uzbekistan,” *Web of Teachers: Inderscience Research*, vol. 3, no. 1, pp. 27–32, 2025. [Online]. Available: https://webofjournals.com/index.php/1/article/view/2837

[34] A. Februadi, Y. Firmansyah, and W. Rafdinal, “Adoption of mobile business applications by MSMEs: Integrating application quality, TOE model and diffusion of innovation,” *Pakistan Journal of Life and Social Sciences*, vol. 23, no. 1, 2025, https://doi.org/10.57239/pjlss-2025-23.1.0010

[35] J. Rudewicz, “Theoretical insights into artificial intelligence applications in human geography and spatial management (GeoAI),” *European Research Studies*, vol. 27, no. 4, pp. 973–984, 2024, https://doi.org/10.35808/ersj/3640

[36] A. Nurbatsin, A. Kireyeva, L. Gamidullaeva, and T. Abdykadyr, “Spatial analysis and technological influences on smart city development in Kazakhstan,” *Journal of Infrastructure, Policy and Development*, vol. 8, no. 2, p. 3012, 2023. [Online]. Available: https://elib.pnzgu.ru/files/eb/X3fVoGRlD6Hu.pdf.

[37] L. Kurmangaziyeva, Z. O. Oralbekova, S. Akhmetzhanova, A. Khassenova, M. Akishev, and T. Zhukabayeva, “Analysis of the problem of ensuring the reliability of the information system,” in *Proc. DTESI*, 2022. [Online]. Available: https://ceur-ws.org/Vol-3382/Paper13.pdf.

[38] S. Morandini, F. Fraboni, M. De Angelis, G. Puzzo, D. Giusino, and L. Pietrantoni, “The impact of Artificial Intelligence on workers’ skills: Upskilling and reskilling in organisations,” *Informing Science*, vol. 26, pp. 039–068, 2023, https://doi.org/10.28945/5078.

[39] N. Kodakandla, “Scaling AI responsibly: Leveraging MLOps for sustainable machine learning deployments,” *International Journal of Science and Research Archive*, vol. 13, no. 1, pp. 3447–3455, 2024, https://doi.org/10.30574/ijsra.2024.13.1.1798.

[40] “World Development Indicators,” *Worldbank.org*. [Online]. Available: https://databank.worldbank.org/source/world-development-indicators. [Accessed: 04-Jun-2025].

[41] A. W. Omer and T. H. Ali, “Dealing with the outlier problem in multivariate linear regression analysis using the Hampel filter,” *Kurdistan Journal of Applied Research*, vol. 10, no. 1, pp. 1–17, 2025, https://doi.org/10.24017/science.2025.1.1.

[42] C. Muthuvelayutham, “Artificial Intelligence–based multiple regression algorithm to indicate human development in the workplace,” *Emperor International Journal of Management*, vol. 2, no. 12. [Online]. Available: https://www.mayas.info/journal-issue/artificial-intelligence-based-multiple-regression-algorithm-indicate-human-1

[43] V. M. Reddy and L. N. Nalla, “The role and impact of artificial intelligence in the insurance sector: Transforming risk assessment, claims processing, and customer experience,” *International Journal of Modern Computing*, vol. 8, no. 1, pp. 1–15, 2025. [Online]. Available: https://yuktabpublisher.com/index.php/IJMC/article/view/214

[44] S. R. Adavelli, “Beyond the claims: Emerging AI models and predictive analytics in property & casualty insurance risk assessment,” *International Journal of Science and Research*, vol. 13, no. 7, pp. 1625–1631, 2024. [Online]. Available: https://philpapers.org/rec/SATBTC

[45] R. K. Srirangam, S. Chennuri, and V. Pendyala, “Technological disruption in P&C insurance: The impact of advanced analytics on risk assessment and customer engagement,” *Technology (IJRCAIT)*, vol. 7, no. 2, 2024. [Online]. Available: https://www.researchgate.net/publication/389635525

[46] I. Buriak, K. Nechyporenko, V. Chychun, H. Polianko, and L. Milman, “Trends in the development of management and business technologies in the context of the modern Ukrainian economy,” *Futurity Economics & Law*, vol. 2, no. 4, pp. 56–77, 2022, https://doi.org/10.57125/FEL.2022.12.25.04.

[47] L. Paul, L. Sadath, and A. Madana, “Artificial intelligence in predictive analysis of insurance and banking,” in *Artificial Intelligence*, CRC Press, 2021, pp. 31–54, https://doi.org/10.1201/9781003095910-4.

[48] M. Eling, D. Nuessle, and J. Staubli, “The impact of artificial intelligence along the insurance value chain and on the insurability of risks,” *The Geneva Papers on Risk and Insurance - Issues and Practice*, vol. 47, no. 2, pp. 205–241, 2022, https://doi.org/10.1057/s41288-020-00201-7.

[49] M. Bellanger and B. A. Engel, *Digital Signal Processing: Theory and Practice*. Wiley, 2024. [Online]. Available: https://books.google.com.pk/books?id=ErL6EAAAQBAJ