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ARTIFICIAL INTELLIGENCE IN THE INSURANCE INDUSTRY: OPPORTUNITIES, BARRIERS AND STRATEGIC PERSPECTIVES

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Abstract. *The research examines the digital transformation of global and national insurance sectors through AI-driven operational models. The study analyses current artificial intelligence (AI) applications across the insurance value chain, identifies principal implementation barriers, and outlines strategic development prospects in the context of global trends and Ukrainian market conditions. The methodology draws on a systematic review of academic literature (2018-2025), authoritative industry reports, and documented InsurTech case studies. The global AI-in-insurance market is projected to reach USD 176 billion by 2035 at a compound annual growth rate of 32.21%. Core technologies, including machine learning, computer vision, and generative AI, are examined with respect to their functional roles across underwriting, claims processing, fraud detection, and customer engagement. Measurable efficiency gains are documented: underwriting accuracy improves by up to 30%, while automated claims processing reduces cycle times by up to 75%. Key barriers to scaled adoption are identified, encompassing legacy system integration, data quality deficits, algorithmic bias, and regulatory compliance requirements under the EU AI Act. The strategic importance of AI for operational resilience is illustrated by the Ukrainian insurance market, which processed nearly one million claims under wartime conditions in 2024 while sustaining premium growth of 18.7%. A strategic framework is proposed centred on data infrastructure investment, explainable AI adoption, and proactive risk prevention models. Differentiated recommendations are developed for insurance executives, regulatory authorities, and researchers. Effective AI governance, integrating ethical safeguards with structured deployment frameworks, constitutes a foundational condition for sustained competitive positioning in an increasingly AI-intensive industry.*

Keywords: *artificial intelligence; insurance industry; digital transformation; underwriting; fraud detection; explainable AI; Ukrainian insurance market; operational resilience.*

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ШТУЧНИЙ ІНТЕЛЕКТ У СТРАХОВІЙ ГАЛУЗІ: МОЖЛИВОСТІ, БАР'ЄРИ ТА СТРАТЕГІЧНІ ПЕРСПЕКТИВИ

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Анотація. *Статтю присвячено вивченню цифрової трансформації глобального та національного страхових секторів через операційні моделі, керовані штучним інтелектом (ШІ). Метою статті є аналіз поточних застосувань ШІ в ланцюжку створення вартості страхових послуг, ідентифікація основних бар'єрів впровадження та окреслення стратегічних перспектив розвитку галузі в контексті глобальних тенденцій та умов українського ринку. Методологічну основу становить систематичний огляд наукової літератури за 2018–2025 рр., авторитетних галузевих звітів та задокументованих кейсів InsurTech-компаній. Встановлено, що обсяг світового ринку ШІ у страхуванні прогнозується на рівні 176 млрд. дол. США до 2035 р. при середньорічному темпі зростання 32,21%. Досліджено ключові технології, зокрема машинне навчання, комп'ютерний зір та генеративний ШІ, з огляду на їх функціональну роль в андеррайтингу, обробці претензій, виявленні шахрайства та взаємодії з клієнтами. Визначено кількісні показники операційної ефективності: точність андеррайтингу зростає до 30%, а автоматизована обробка претензій скорочує тривалість циклів до 75%. Окреслено ключові бар'єри масштабування, що охоплюють інтеграцію із застарілими системами, дефіцити якості даних, алгоритмічну упередженість та вимоги регуляторної відповідності відповідно до Закону ЄС про ШІ. Стратегічне значення ШІ для операційної стійкості проілюстровано на прикладі українського страхового ринку, який в умовах воєнного стану у 2024 р. опрацював близько одного мільйона претензій, забезпечивши при цьому зростання премій на 18,7%. Запропоновано стратегічну концептуальну модель, що базується на інвестиціях в інфраструктуру даних, впровадженні пояснюваного ШІ та розбудові проактивних моделей запобігання ризикам. Сформульовано диференційовані рекомендації для страховиків, регуляторних органів та дослідників. Ефективне управління ШІ, яке поєднує етичні гарантії зі структурованими механізмами впровадження, є базовою умовою стійкого конкурентного позиціонування в умовах дедалі більшої технологічної насиченості галузі.*

Ключові слова: *штучний інтелект; страхова галузь; цифрова трансформація; андеррайтинг; виявлення шахрайства; пояснюваний ШІ; страховий ринок України; операційна стійкість.*

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1. Introduction

The global insurance industry, a key component of global financial systems and risk management infrastructure, is undergoing a significant phase of digital transformation driven by the rapid growth of data availability, evolving customer expectations, and continuous technological innovation. Traditional actuarial approaches, largely based on historical statistical models and aggregated risk indicators, are increasingly challenged by the growing complexity and dynamic nature of contemporary risks, including climate change, cyber threats, and geopolitical instability. These developments require insurers to adopt more advanced analytical tools capable of processing large volumes of heterogeneous data and supporting data-driven decision-making processes.

Artificial intelligence (AI), encompassing Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Computer Vision (CV), and Generative AI (GenAI), has become a structurally significant driver reshaping core insurance functions. AI enables significant changes in risk assessment and decision-making processes: from reactive loss compensation toward proactive risk prediction, prevention, and individually tailored coverage [1; 2]. Market projections underscore this momentum: the global AI-in-insurance market was valued at approximately USD 10.82 billion in 2025 and is forecasted to reach USD 176.58 billion by 2035, representing a compound annual growth rate (CAGR) of 32.21% [3].

Adoption metrics indicate accelerating integration across the value chain. By mid-2025, 76% of insurance organizations had deployed generative AI capabilities in at least one business function, although scaled enterprise-wide implementation remains limited [4]. The operational impact is substantial: AI-driven claims processing has reduced turnaround times by 55–75%, shortening routine claim cycles from 7–10 days to under two days [5]. Furthermore, fraud detection capabilities have improved by up to 65%, accompanied by a 60% reduction in overpayment rates, with the potential to mitigate losses for property and casualty insurers by USD 80–160 billion by 2032 [6].

In the Ukrainian context, the full-scale invasion in February 2022 and the subsequent withdrawal of international reinsurers created unprecedented operational pressures. Nevertheless, digital transformation, accelerated by wartime exigencies, has contributed to the resilience of the non-bank financial sector, which saw sustained asset growth in recent years. AI tools have proven critical in supporting remote underwriting, claims handling, and resilience modeling [7; 8]. This study examines these global and local dynamics to provide a strategic roadmap for AI integration in the insurance sector.

2. Literature review, shortcomings and problem statement

Research on AI in insurance has expanded steadily since 2018 and gained significant momentum after 2020, driven by rapid digitalisation across financial services, the proliferation of alternative data sources, and the emergence of generative AI.

Eling and Lehmann (2018) [9] provide one of the earliest systematic examinations of the field, analysing 84 academic papers and 22 industry reports through Porter’s value chain

framework and Berliner's insurability criteria. Their findings indicate that AI lowers operational costs, generates new revenue streams, and shifts the sector's orientation from reactive loss compensation toward predictive risk prevention, though they also caution that certain risk categories may become harder to insure as AI-driven prevention alters underlying frequency and severity distributions. This foundational tension between efficiency gains and insurability boundaries remains a recurring theme in subsequent literature.

Bibliometric analyses of the broader field confirm this trajectory: Pattnaik et al. [10] identify insurance-related AI as one of the fastest-growing sub-streams within financial technology research, noting a near-tripling of annual publication output between 2019 and 2023, with fraud detection, underwriting automation, and customer analytics constituting the dominant thematic clusters.

Kumar et al. [11], in a dedicated bibliometric mapping of AI and ML research specifically within insurance, corroborate this pattern and identify underwriting automation, fraud analytics, and customer experience as the three principal application clusters, while noting a structural underrepresentation of emerging market contexts in the published evidence base. A domain-specific scientometric examination by Atlasi et al. [12], covering 847 publications on AI applicability in insurance, further identifies explainability, regulatory compliance, and data governance as the most rapidly emerging research fronts.

Bhattacharya et al. [1] offer a comprehensive bridge between theoretical frameworks and real-world implementation, covering risk management, underwriting, claims handling, and customer interaction across multiple lines of business. Their analysis is notable for foregrounding the persistent gap between academic research and industrial adoption: they document that while ML-based underwriting models outperform actuarial benchmarks in controlled studies, fewer than half of surveyed insurers had moved beyond piloting to scaled deployment as of 2024, a finding consistent with the broader financial services sector, where analogous adoption gaps between piloting and scaled deployment have been documented across banking operations including fraud detection, credit scoring, and customer service automation [13; 14]. Gupta et al. [15] complement this perspective by introducing an AI adoption framework grounded in the technology-organisation-environment (TOE) model, identifying top management support, financial readiness, and regulatory environment as the three most significant determinants of adoption intent, emphasising organisational preparation and capability development as prerequisites for sustained deployment, rather than technology selection alone.

Fraud detection has attracted extensive dedicated investigation within the insurance AI literature. Systematic reviews document the increasing use of supervised, unsupervised, and hybrid ML models in claims analysis, delivering accuracy improvements of 20–30% over rule-based approaches [16]. Graph neural network architectures, in particular, have demonstrated superior performance in identifying organised fraud rings by mapping relational patterns across claimants, service providers, and legal representatives − a capability unavailable to conventional anomaly detection systems. Persistent methodological challenges include inconsistent data quality across legacy claims systems, privacy restrictions that limit cross-institutional data sharing, and the structural scarcity of labelled fraudulent examples, which constrains supervised model training.

Underwriting and risk assessment benefit from ensemble methods and alternative data sources. Studies demonstrate that gradient boosting algorithms (XGBoost, Random

Forest, and their variants) often paired with explainability tools such as SHAP and LIME, improve prediction of medical insurance costs and mortality risk while maintaining the interpretability required for regulatory compliance and adverse-action notification [17; 18]. Telematics, wearables, and IoT sensor inputs enable usage-based and behaviour-based products that move beyond static demographic rating factors toward continuous, individualised risk profiling [3].

Claims processing benefits substantially from CV and NLP. DL architectures reduce handling times significantly and facilitate visual anomaly detection for fraud screening in motor and property lines [5; 19].

In health insurance, AI supports fraud, waste, and abuse detection, financial management, risk modelling, and value-based care initiatives, though ethical concerns around data privacy, algorithmic bias, and the potential for discriminatory outcomes in coverage decisions remain prominent [20]. Customer service and personalisation increasingly rely on conversational agents and recommendation engines that deliver continuous support and measurably higher satisfaction levels, with 67% of global insurers reporting chatbot deployment by mid-2025 [3].

The regional and crisis-context literature adds an important dimension to the global evidence base. Shevchuk et al. [23] describe the COVID-19 pandemic as a structural catalyst for digital transformation in Ukrainian insurance, particularly accelerating remote underwriting and claims management capabilities that proved foundational for the subsequent wartime adaptation. Fedorovych et al. (2025) examine opportunities and barriers to AI adoption in insurance services under conditions of geopolitical disruption, documenting gains in operational resilience and identifying institutional capacity constraints as the binding limitation. Hrabovskyi [8] and Pletneva & Zagorska [24] address wartime and social insurance adaptations respectively, proposing ethical frameworks for AI deployment aligned with emerging EU norms, a contribution that anticipates the regulatory convergence pressures Ukrainian insurers will face as part of the EU accession process.

Several challenges recur with remarkable consistency across the literature regardless of geographic context or insurance line. Model opacity necessitates explainable AI frameworks capable of generating human-interpretable justifications for underwriting and claims decisions [18]. Historical training data can entrench and amplify demographic biases present in legacy actuarial practices [21].

Privacy regulations constrain the granularity of data that can lawfully be incorporated into predictive models [22]. Legacy core systems impose substantial integration costs and delay the realisation of AI’s operational potential [6].
Finally, regulatory frameworks across most jurisdictions have not kept pace with the speed of technological change, creating compliance uncertainty that inhibits investment in frontier applications. These convergent findings underscore both AI's transformative potential for the insurance sector and the necessity for governance frameworks commensurate with that potential.

3. Unresolved aspects of the general problem

Despite the substantial expansion of the insurance AI literature documented above, several critical dimensions remain insufficiently addressed. Longitudinal evidence on the long-term effects of AI-driven underwriting on market concentration, competitive

dynamics, and the insurability of vulnerable populations is virtually absent: most existing studies present cross-sectional snapshots of operational performance gains rather than sustained empirical assessments of structural market consequences, leaving open the question of whether efficiency improvements translate into durable competitive advantages or accelerate commoditisation at the expense of coverage accessibility.

Comparative analyses of AI adoption across heterogeneous regulatory regimes, particularly between highly regulated European markets operating under GDPR and the EU AI Act, and emerging economies with nascent digital governance frameworks, remain sparse, a gap especially pronounced in markets experiencing acute geopolitical disruption, such as Ukraine, where digitalisation has been driven by crisis necessity rather than strategic design.

The intersection of algorithmic fairness and actuarial ethics has received theoretical attention, yet empirically grounded evaluation of real-world outcomes remains limited: the opacity of proprietary models constrains independent auditing, and the absence of standardised explainability benchmarks prevents meaningful cross-institutional comparison [18; 21].

Finally, research on the human capital dimensions of AI adoption, including skill transition pathways for actuaries and claims professionals in an increasingly automated environment, remains fragmented across disciplines and disconnected from insurance-specific organisational evidence. The present study addresses these gaps by synthesising global technological trends with an empirical case study of the Ukrainian insurance market's crisis-driven operational resilience, thereby contributing both a developed-market analytical framework and an underrepresented emerging-market perspective to the field.

4. Research objectives

This article provides a comprehensive analysis of current AI applications in the insurance industry, delineates the principal technical, organisational, and regulatory challenges constraining scaled adoption, and explores future development prospects. Drawing on a systematic review of academic literature covering the period 2018–2025, authoritative industry reports, and documented case studies of leading global and regional insurers, it synthesises actionable insights for three principal audiences: insurance executives and boards navigating strategic transformation, regulatory authorities shaping governance frameworks, and researchers advancing AI methodologies tailored to the operational and ethical specificities of insurance contexts.

5. The main material research

The application of AI in insurance has developed through distinct technological phases, each progressively transforming risk assessment, policy pricing, underwriting, claims processing, and customer service. The sector, historically reliant on actuarial science and statistical modelling, has long been an early adopter of computational tools, a structural disposition that has facilitated its readiness for AI integration at scale.

The adoption of AI in insurance does not occur uniformly across organisations or markets. Empirical evidence and industry diagnostics consistently identify a maturity continuum along which insurers progress from isolated experimentation to enterprise-wide transformation, a progression shaped by data infrastructure quality, organisational readiness, regulatory environment, and capital availability. Understanding this continuum

is essential for setting realistic implementation timelines, allocating investment efficiently, and benchmarking organisational positioning against industry peers. Table 1 presents a five-stage AI maturity model synthesised from the academic and industry literature.

Table 1

AI implementation maturity stages in insurance

Stage	Designation	Horizon	Characteristic Features	Priority Use Cases	Key Constraints
1	Ad hoc experimentation	0-6 months	Isolated pilots in individual business units; no governance; fragmented data; outcomes unmeasured	Chatbots, basic claims routing	Absent data strategy; no executive ownership
2	Structured piloting	6-18 months	Dedicated AI teams or centres of excellence; initial data lake consolidation; defined KPIs; governance framework introduced	Fraud scoring, underwriting assist, NLP document extraction	Legacy system interfaces; pilot-to-scale transition gap
3	Scaled deployment	18-36 months	AI embedded in core workflows across ≥2 business lines; 40-60% of routine claims processed without human intervention; real-time fraud scoring at submission	STP claims, dynamic pricing, telematics-based UBI	Integration costs; talent shortage; model explainability requirements
4	Enterprise integration	3-5 years	AI permeates full value chain from product design through reserving; XAI embedded by design; federated learning operational; dynamic pricing engines adjust in near-real time	Full value chain AI, personalised health/life products, automated regulatory reporting	Model risk governance; data sovereignty; regulatory compliance overhead
5	Ecosystem orchestration	5+ years	Insurer operates as a data and risk platform integrating IoT manufacturers, healthcare providers, mobility operators, and reinsurers; synthetic data supplements scarce actuarial datasets for emerging risk categories	Embedded insurance, parametric smart contracts, genomics-linked health products	Systemic risk from model correlation; third-party AI dependency; regulatory frameworks not yet developed

Source: compiled by authors based on [1; 3; 4; 15]

The maturity model reveals several structural patterns with direct implications for strategy and policy. Progression across stages is neither linear nor guaranteed: organisations

frequently stall between Stage 2 and Stage 3, the most consequential transition in the model, due to the compounding effects of legacy core system incompatibility, data quality deficits, and the absence of board-level AI ownership. Gupta et al. [15] identify top management support, regulatory environment, and financial readiness as the three strongest predictors of successful Stage 3 attainment, accounting for more variance in adoption outcomes than technology spending alone. This finding is consistent with the broader financial services AI literature, where organisational readiness factors systematically outperform technology capability as determinants of scaled deployment [13; 10].

By mid-2025, approximately 38% of global insurers with gross written premiums exceeding USD 1 billion had reached Stage 3 or beyond, while the majority of mid-market and regional carriers remained at Stages 1–2 [4]. This distribution reflects both the capital intensity of legacy modernisation and the concentration of AI talent in large urban markets and digitally mature economies. Digital-native InsurTechs, Lemonade, Root, Oscar Health, effectively entered the market at Stage 3 or 4, unburdened by legacy infrastructure, which partially explains their disproportionate influence on industry benchmarks relative to their premium volumes.

The Ukrainian insurance market presents a structurally atypical maturity trajectory. Prior to February 2022, most domestic carriers operated at Stages 1–2, with digitalisation proceeding at a pace characteristic of emerging European markets. The full-scale invasion compressed Stages 1 and 2 into an atypically abbreviated window: physical office inaccessibility, the displacement of over eight million civilians, and the withdrawal of international reinsurers collectively forced a crisis-driven acceleration of digital customer service infrastructure.

As a result, operational AI maturity in customer-facing processes, mobile claims submission, chatbot triage, telemedicine routing, advanced rapidly, creating a structural paradox in which front-end digital capability outpaces back-end data governance and model risk management maturity. This decoupling represents both a near-term vulnerability and a distinctive development pathway that merits longitudinal examination as the market stabilises in the post-war reconstruction period.

The contemporary insurance industry deploys a diverse portfolio of AI technologies, each addressing specific operational needs from risk modelling to customer interaction, and these technologies increasingly integrate synergistically to create comprehensive systems that surpass isolated capabilities. Table 2 provides a structured overview of the principal technologies and their primary insurance applications.

ML and DL underpin most AI applications in insurance, processing structured and unstructured data from telematics streams, medical records, and satellite imagery. NLP transforms text-heavy workflows such as policy interpretation, claims documentation, and customer service.

CV enables efficient damage assessment through automated photo and video analysis. Predictive analytics modernises actuarial practice, while generative AI supports policy drafting, personalised communication, and synthetic data generation for privacy-compliant model training.

Explainable AI addresses regulatory demands for transparency and bias detection; federated and edge AI tackle privacy constraints and real-time processing requirements respectively.

Successful implementation of this technology portfolio requires robust data infrastructure, cross-functional governance, and sustained ethical alignment – conditions that, as the literature reviewed above demonstrates, remain unevenly met across the industry.

Table 2

Key AI technologies used in insurance

AI Technology	Core Description	Primary Insurance Applications
Machine Learning (ML)	Algorithms that learn patterns from structured and unstructured data (supervised, unsupervised, reinforcement learning)	Risk scoring, pricing, segmentation, churn prediction, fraud detection
Deep Learning (DL)	Multi-layer neural network architectures (CNNs, RNNs, Transformers)	Damage assessment, medical/text analysis, premium estimation
Natural Language Processing (NLP)	Techniques for processing and understanding human language	Claims document processing, chatbots, policy analysis, sentiment
Computer Vision (CV)	Methods for automated interpretation of visual data (CNNs, object detection)	Photo/video damage assessment, property inspection, KYC
Predictive Analytics	Forecasting using statistical and ML models	Claims frequency/severity, lapse prediction, catastrophe modeling
Generative AI	Generation of synthetic content and data using generative models (LLMs, GANs)	Policy drafting, personalized communication, synthetic data
Robotic Process Automation (RPA) + AI	Intelligent automation of repetitive and rule-based business processes	Policy administration, billing, regulatory reporting
Explainable AI (XAI)	Methods for interpreting and explaining machine learning model outputs (SHAP, LIME)	Regulatory compliance, bias detection, transparent decisions
Federated Learning	Distributed ML approach enabling collaborative model training without data sharing	Collaborative fraud detection, secure health data analysis
Edge AI	Execution of AI models on local devices for real-time processing	Telematics analysis, IoT risk alerts, mobile assessments

Source: compiled by authors based on [3; 5; 15; 18; 19]

Figure 1 illustrates the conceptual architecture of an AI-enabled digital health insurance system, situating the principal technological components within their operational and regulatory context. The framework integrates heterogeneous data inputs (electronic health records, wearable sensor outputs, telemedicine consultation records, and administrative insurance datasets) into a layered processing structure in which dedicated machine learning modules perform risk prediction, fraud detection, automated claims assessment, and clinical triage in parallel rather than in sequence, thereby reducing both processing latency and the manual coordination costs associated with siloed legacy workflows.

A structurally significant feature of the architecture is the intermediary function assigned to telemedicine platforms, which serve as the primary interface connecting patients, healthcare providers, and insurance operations – a configuration that proved operationally critical in the Ukrainian wartime context, where physical access to providers was severely constrained.

Consistent with the regulatory requirements of the EU AI Act and emerging ethical standards for high-risk medical AI systems, the framework positions algorithmic outputs as decision-support inputs subject to human review rather than as autonomous determinations, preserving the accountability structures that regulators and policymakers have identified as prerequisites for responsible deployment across the insurance value chain.

AI permeates the entire insurance value chain, enhancing efficiency, accuracy, and customer value across core operational processes. Table 3 maps principal applications to dominant AI technologies and leading industry implementers.

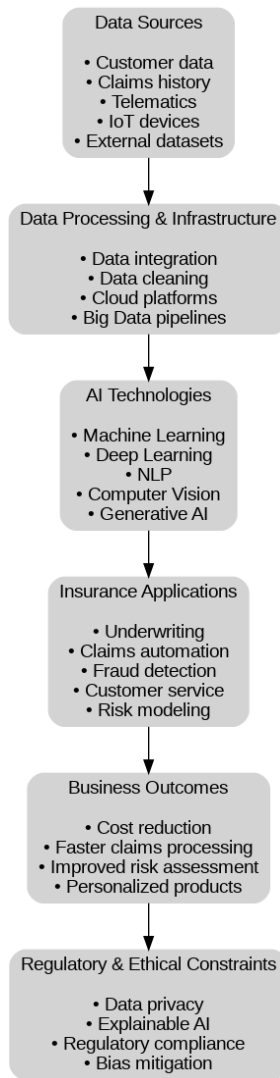


Fig 1. Conceptual framework of AI integration in the insurance industry
Source: designed by the authors based on [7; 20; 22; 18]

While Tables 2 and 3 address AI applications across functional processes, the operational context and regulatory constraints of individual insurance lines create materially distinct implementation profiles. Life, non-life (property and casualty), and health insurance differ in data availability, claim frequency, regulatory scrutiny, and risk horizon, each dimension shaping how AI technologies are prioritised, governed, and evaluated.

The life insurance segment is characterised by long policy durations, low claim frequency, and high dependence on mortality and morbidity modelling. AI's primary contribution lies in underwriting transformation and policyholder engagement. Traditional life underwriting relies on medical examinations, blood panels, and self-reported health histories – a process spanning weeks and costing insurers an estimated USD 125-350 per applicant [3].

ML-based accelerated underwriting models, trained on electronic health records, pharmacy data, wearable biometrics, and behavioural signals, now enable real-time policy issuance for a growing subset of applicants. John Hancock's Vitality programme demonstrated that wearable-integrated dynamic underwriting improves mortality prediction accuracy by up to 30% while reducing lapse rates by 15% through behavioural engagement incentives [3].

Generative AI is reshaping product design: LLM-assisted policy drafting reduces documentation cycles from days to hours, and conversational AI enables needs-based selling that adapts recommendations to individual life stage and financial profile in real time. However, life insurance faces distinct algorithmic fairness challenges, mortality prediction models trained on historical data can perpetuate socioeconomic disparities in pricing, and several EU member states have restricted the use of genetic data in underwriting entirely [21].

Table 3

Main AI Applications in Insurance – Technologies, Tasks, and Leaders

Insurance Process	Key AI Technologies	Leading Companies / Solutions
Risk Assessment &	ML, Predictive Analytics, Telematics, IoT	Progressive (Snapshot), Lemonade, Root, Ping An
Claims Processing &	Computer Vision, NLP, DL, RPA	Tractable, Lemonade, Aviva, Allianz, Zurich
Fraud Detection & Prevention	Anomaly Detection, ML, Graph Neural Networks	Shift Technology, FICO, Coalition, SAS
Customer Service &	NLP, Chatbots, Sentiment Analysis	Lemonade (AI Jim), Geico, Allstate, USAA
Pricing Optimization	ML, Predictive Analytics	Progressive, Allstate (Arity), Metromile
Damage Assessment	Computer Vision, DL (CNNs)	Tractable, Snapsheet, Tokio Marine
Risk Prevention & Mitigation	IoT, Predictive Analytics, ML	John Hancock (Vitality), Hippo, Discovery
Product Innovation	Generative AI, Recommendation Systems	Lemonade, Oscar Health

Source: compiled by authors based on [1; 3; 5; 19]

Non-Life (Property and Casualty) Insurance lines generate the highest volumes of structured AI-relevant data (telematics streams, satellite imagery, IoT sensor feeds, repair estimates, and police reports) and consequently represent the most advanced AI deployment frontier. Claims automation has progressed furthest in motor insurance, where computer vision models assess vehicle damage from smartphone photographs with accuracy rates exceeding 95% and processing times under 15 minutes [19].

Aviva's deployment of over 80 AI models in claims operations shortened liability assessment cycles by 23 days, improved routing accuracy by 30%, and generated savings exceeding £60 million in 2024 while reducing customer complaints by 65% [3].

Property insurance benefits from aerial and satellite imagery analysis for catastrophe loss estimation, compressing post-event assessment cycles from weeks to hours and enabling parametric trigger verification at scale.

Fraud presents a particularly acute challenge in non-life lines, where organised rings account for an estimated 10–15% of total claims costs in some European markets; graph neural network models mapping relationships between claimants, repair shops, and legal representatives identify coordinated fraud patterns that rule-based systems miss entirely, with Shift Technology reporting detection improvements of 300% over legacy approaches alongside simultaneous reductions in false positive rates [3].

Usage-based insurance in motor lines represents perhaps the most mature AI-enabled product innovation: Progressive's Snapshot programme, drawing on over 30 billion miles of telematics data, demonstrated that behavioural pricing reduces loss ratios by 10–15 percentage points relative to demographic-only models while attracting lower-risk drivers through premium discounts of 10–30% [3].

Health insurance operates at the intersection of AI's highest potential and its most contested ethical terrain. The density of health data, claims histories, diagnostic codes, pharmaceutical records, genomic markers, wearable outputs, and social determinants, provides exceptional model training material, while simultaneously imposing the strictest privacy and non-discrimination regulations across any insurance line.

AI's most documented contribution is fraud, waste, and abuse detection: supervised ML models trained on billing patterns identify upcoding, phantom billing, and unnecessary procedures with accuracy improvements of 20–35% over rule-based auditing, generating savings estimated at USD 30–40 billion annually in US federal programmes alone [20].

Predictive models for high-cost claimant identification enable care management interventions before hospitalisation, reducing avoidable admissions by 15–20% in documented programmes [20]. NLP applied to clinical notes enables automated prior authorisation processing, compressing review cycles from days to minutes and reducing administrative costs that currently consume 25–30% of US health insurance premiums.

In the Ukrainian context, AI-enabled telemedicine integration proved operationally critical during the full-scale war, with chatbot triage systems routing patients to available providers amid infrastructure disruption and the displacement of over eight million civilians affecting network accessibility [7].

The ethical boundaries of health AI remain actively contested: predictive models for chronic disease risk can improve preventive care targeting, but their use in underwriting

decisions risks systematic exclusion of high-risk individuals – a tension that the EU AI Act addresses by classifying certain health scoring models as high-risk systems requiring mandatory conformity assessment and human oversight before deployment.

AI integration in insurance yields substantial operational benefits alongside significant structural challenges. Table 4 contrasts the principal advantages and obstacles across the value chain.

Table 4

Benefits and challenges of AI in insurance

Benefits	Challenges
Risk accuracy +25-30% (telematics, ML models)	Data quality – incomplete/siloed legacy data
Claims time – 55-75% (<2 days routine)	Legacy integration – costly core system upgrades
Fraud detection +65%, overpayments – 60% ($80-160B savings by 2032)	Regulatory uncertainty – GDPR/EU AI Act gaps
Cost reduction – 20-50% (underwriting/claims)	Algorithmic bias – perpetuation of historical discrimination
Personalization & NPS +10-15% (chatbots, 90% + satisfaction)	Explainability – black box opacity
STP for 70% simple claims, efficiency +70%	Privacy/cyber risks – vulnerabilities from granular data
New products (parametric, embedded insurance)	Talent shortage – competition for AI specialists
Proactive prevention (IoT, 40% better forecasting)	Model drift / ethics – maintenance, employment impact

Source: compiled by authors based on [3; 5; 18; 27]

The benefits documented in the literature are substantial and consistently replicated. Underwriting accuracy improves by 25–30% through telematics and wearable integration [3]. Claims processing times decrease by 55–75%, with routine claims resolved in under two days compared to the industry baseline of 7–10 days, while costs decline by up to 20% and Net Promoter Scores improve by 10–15% [5].

Fraud detection rates improve by 65%, overpayment rates fall from approximately 10% to 4%, and the potential cumulative savings for property and casualty lines reach USD 80–160 billion by 2032 [6]. IoT-enabled risk prevention improves catastrophe forecasting accuracy by 40%, repositioning insurers from passive loss compensators toward active risk management partners [27].

The challenges, however, are equally consistent. Fragmented legacy data systems constrain model performance regardless of algorithmic sophistication [6]. Core system integration requires capital-intensive modernisation that most mid-tier insurers cannot absorb without external support. Algorithmic bias embedded in historical training data risks perpetuating demographic discrimination in pricing and coverage decisions without systematic explainability frameworks [18].

Regulatory uncertainty, particularly the evolving interaction between GDPR, the EU AI Act, and national supervisory requirements, generates compliance costs that disproportionately burden smaller market participants [21; 22]. Talent shortages in the

intersection of actuarial science and ML competency, and broader ethical concerns around employment displacement and the erosion of human judgement in high-stakes decisions, constrain both the pace and quality of scaled adoption.

Ukraine's insurance sector provides a distinctive empirical illustration of AI as an operational necessity rather than a discretionary efficiency instrument. Following the February 2022 full-scale invasion and the subsequent withdrawal of international reinsurers, digitalisation became essential for market continuity. UNIQA Ukraine processed nearly one million claims, including 350,000 health claims, in 2024 through the AI-enhanced myUNIQA mobile application, integrated Chabot systems, and telemedicine infrastructure; gross written premiums grew 18.7% to UAH 47 billion despite wartime conditions [25].

The EBRD's €110 million Ukraine Recovery and Reconstruction Guarantee Facility, launched in December 2024, enabled war-risk reinsurance with potential annual capacity of €1 billion, providing a structural mechanism for market stabilisation [26]. Ukraine's technology ecosystem, comprising 243 AI companies and over 300,000 IT specialists, supports continued innovation, positioning the market as a regional reference case for crisis-driven digital transformation [7; 8]. The Ukrainian experience underscores a finding with broader applicability: digital investment in insurance delivers not only operational efficiency but institutional resilience under conditions of acute systemic disruption.

The evidence synthesised across the preceding sections supports a set of differentiated strategic recommendations directed at the two principal actor groups whose decisions will determine the trajectory of AI adoption in insurance. These recommendations are grounded in the operational, regulatory, and organisational patterns documented throughout the literature and illustrated by the case material examined above, and are intended to move beyond generic calls for digital transformation toward the specific governance, investment, and capability conditions that distinguish sustained value creation from accelerated technical debt accumulation.

For insurance executives and boards, the central strategic imperative is to recognise AI adoption as an organisational transformation challenge rather than a technology procurement exercise. The maturity evidence reviewed above consistently demonstrates that the binding constraints on scaled deployment are not algorithmic, they are institutional: data infrastructure quality, board-level accountability structures, talent pipeline development, and the organisational capacity to govern models that operate at the intersection of commercial incentive, actuarial risk, and regulatory obligation. Organisations that have successfully progressed beyond the piloting stage share a common structural characteristic: AI governance is treated as a first-order strategic function with dedicated executive ownership, adequate resourcing, and direct board visibility, not as a sub-function of IT delivery. With this framing in mind, the following recommendations address the five most consistently documented determinants of successful scaled AI adoption across the global insurance industry:

1. Establish AI governance as a board-level accountability. The most significant predictor of successful scaled AI adoption is executive ownership rather than technology investment alone [15]. Boards should appoint a Chief AI Officer or equivalent accountable for model risk management, algorithmic fairness oversight, and AI ethics policy, separate from the CTO function, which tends to prioritise capability over governance.

2. Invest in data infrastructure before model sophistication. Industry evidence consistently demonstrates that data quality limitations, fragmented legacy systems, inconsistent labelling, and siloed business unit databases, constrain AI performance more than algorithmic design choices [6]. Insurers should allocate a minimum of 40% of their AI investment budgets to data engineering, governance platforms, and master data management before expanding model portfolios.

3. Adopt a portfolio approach to AI use cases. Organisations should maintain a balanced pipeline across three horizons: (i) short-term operational efficiency plays with proven ROI (claims triage, fraud flagging, chatbots); (ii) medium-term differentiation initiatives (telematics-based personalisation, accelerated underwriting); and (iii) long-term structural investments (ecosystem orchestration, parametric product platforms). Concentrating investment exclusively in quick wins depresses long-term competitive positioning; overweighting transformative initiatives without near-term returns erodes board confidence and funding sustainability.

4. Embed explainability from design, not as post-hoc retrofit. Regulatory pressure from the EU AI Act and equivalent national frameworks is accelerating, and models deployed without built-in interpretability will require expensive remediation. SHAP-based feature attribution, counterfactual explanations, and natural-language decision summaries should be standard components of underwriting and claims AI from initial deployment.

5. Build talent through partnerships rather than pure recruitment. The global shortage of actuaries with ML competency and data scientists with insurance domain knowledge cannot be resolved through external hiring alone. Strategic partnerships with universities, participation in industry AI consortia, and structured internal reskilling programmes, particularly for claims handlers, underwriters, and actuaries – offer more sustainable capability development pathways [4].

For regulatory authorities, the central challenge is to construct governance frameworks that are simultaneously robust enough to protect consumers and financial system stability, and adaptive enough to avoid stifling the operational innovation that the evidence reviewed above demonstrates delivers material societal value, faster claims resolution, more accurate fraud detection, greater coverage accessibility, and improved resilience under crisis conditions.

The asymmetry between the pace of AI deployment and the pace of regulatory framework development, documented consistently across the literature [21; 22], creates a structural risk in which neither outcome is achieved: insufficiently specific guidance leaves harmful practices unaddressed, while overly prescriptive requirements applied to rapidly evolving technologies generate compliance costs that disproportionately burden smaller market participants without meaningfully improving consumer outcomes.

The Ukrainian experience is instructive in this regard – the National Bank of Ukraine's pragmatic approach of establishing cybersecurity and operational continuity requirements for non-bank financial institutions ahead of comprehensive AI-specific regulation enabled the digital acceleration documented above while preserving supervisory oversight of systemic risk. The following four recommendations address the governance gaps most consistently identified in the global insurance AI literature as limiting both responsible adoption and effective supervision:

1. Develop insurance-specific AI regulatory guidance. Generic AI governance frameworks such as the EU AI Act provide foundational principles but lack the actuarial and insurance-specific granularity needed for effective oversight. Regulators should develop supplementary guidance addressing permissible data inputs for underwriting, mandatory bias testing methodologies for protected characteristics, and minimum explainability standards for adverse underwriting decisions, drawing on the National Bank of Ukraine's updated non-bank financial institution cybersecurity requirements as a regional model [22].

2. Establish regulatory sandboxes with structured evaluation protocols. Controlled innovation environments allow insurers to test novel AI-enabled products, particularly parametric, embedded, and behaviour-based offering, without full regulatory compliance overhead, provided that consumer protection safeguards are maintained. Sandbox participation should require structured outcome reporting to build the evidence base for future rule-making.

3. Promote international regulatory harmonisation. Divergent national AI governance frameworks create compliance complexity for internationally operating insurers and reinsurers, and may generate regulatory arbitrage that undermines consumer protection standards. Coordination through the International Association of Insurance Supervisors (IAIS) and the Financial Stability Board (FSB) should prioritise common minimum standards for algorithmic transparency and cross-border data sharing frameworks.

4. Address systemic risk from correlated AI models. As insurers increasingly rely on similar third-party AI platforms and training datasets, the risk of correlated model failures, producing simultaneous mispricing, discriminatory outcomes, or claims processing disruptions across multiple carriers, grows materially. Regulators should introduce model diversity requirements analogous to concentration limits in investment portfolios, requiring insurers above defined premium thresholds to demonstrate that their AI underwriting models are not all dependent on a single external data or model provider.

Future Perspectives. AI in insurance is evolving toward fundamental shifts in product design, risk management, and customer interaction. Several convergent trends are reshaping competitive dynamics across the sector and warrant systematic attention from both practitioners and researchers.

Hyper-personalisation and dynamic pricing will become the industry standard. Continuous data streams from IoT devices, wearables, and connected vehicles will enable real-time risk profiles and premiums that adjust to behavioural or environmental changes, while proactive nudging through digital interfaces reinforces risk prevention and repositions insurers as active participants in policyholder risk management [3].

Generative AI will expand into increasingly sophisticated operational tasks. Large language models will automate policy drafting, customer communications, regulatory document analysis, and synthetic data generation for privacy-compliant model training – substantially reducing the manual effort required for content generation and administrative processing [5].

Privacy-preserving architectures will gain prominence as regulatory pressure intensifies. Federated learning will support collaborative model training across insurers without sharing sensitive customer data, enabling multi-party fraud detection and cross-border

regulatory compliance. Edge AI will deliver low-latency processing on end devices, reducing cloud infrastructure dependency and enhancing data security at the point of collection [4; 18].

Quantum computing, though still pre-commercial in most insurance applications, promises material breakthroughs in catastrophe modelling, portfolio optimisation, and large-scale fraud network analysis, significantly improving accuracy for the high-severity, low-frequency risk categories that remain the most actuarially challenging [27].

Embedded and contextual insurance will expand as AI enables direct integration of coverage into non-insurance transactions (e-commerce, mobility platforms, logistics) with instant risk assessment and pricing for parametric, on-demand, and micro-insurance products [3]. Explainable AI will increasingly be embedded from the design stage rather than retrofitted: natural-language decision explanations, counterfactual analysis, and automated bias audits will align models with the EU AI Act, National Bank of Ukraine standards, and equivalent frameworks, while strengthening policyholder trust [21].

Convergence with adjacent technologies will create entirely new insurance categories. AI combined with blockchain will enable autonomous parametric smart contracts with tamper-proof trigger verification; IoT ecosystems will support real-time, prevention-oriented underwriting; genomic data integration will facilitate highly personalised health and life products, subject to the ethical and regulatory constraints documented above [27]. Critically, widespread AI adoption may itself introduce systemic risks, correlated model failures, adversarial attacks on shared training infrastructure, and concentration risk from dependency on a small number of third-party AI platform providers. Future regulatory and governance frameworks will need to address model diversity requirements, mandatory stress testing, and AI-specific concentration limits as structural safeguards against sector-wide vulnerabilities.

6. Conclusions

This study demonstrates that AI has transitioned from an experimental instrument to a core strategic driver across the insurance value chain, delivering measurable and consistently replicated operational gains in underwriting accuracy, claims processing efficiency, fraud detection, and customer engagement. The global AI in insurance market, valued at USD 10.82 billion in 2025 and projected to reach USD 176.58 billion by 2035 at a CAGR of 32.21%, reflects not speculative enthusiasm but the compounding returns of scaled deployment across a sector whose data density, process standardisation, and actuarial tradition have made it structurally receptive to AI integration [3; 4].

The principal empirical findings of this study may be summarised as follows. Underwriting accuracy improves by 25-30% through telematics and wearable integration, with assessment time and costs reduced by up to 90% and 50% respectively. Claims processing times decrease by 55-75%, routine cases resolved in less than two days, with associated cost reductions of up to 20%. Fraud detection rates improve by 65%, generating potential cumulative savings of USD 80-160 billion for property and casualty lines by 2032. These gains are not uniformly distributed: they accrue disproportionately to organisations that have progressed beyond Stage 2 of the AI maturity continuum, where data infrastructure investment, board-level governance accountability, and explainability frameworks are institutionalised rather than aspirational.

The challenges identified are equally consistent across regulatory contexts and insurance lines. Data quality deficits in legacy systems, algorithmic bias embedded in historical training data, the opacity of proprietary models, integration costs that disproportionately burden mid-market carriers, regulatory frameworks that have not kept pace with deployment velocity, and talent shortages at the intersection of actuarial science and machine learning collectively constitute the structural barriers that separate the industry's documented potential from its realised performance. Addressing these barriers requires coordinated action by insurers, regulators, and the research community, no single actor group possesses the authority, resources, or knowledge base to resolve them unilaterally.

The Ukrainian insurance market contributes a distinctive and underrepresented empirical dimension to the global evidence base. Crisis-driven digitalisation following the February 2022 invasion demonstrated that AI tools, mobile claims platforms, chatbot triage systems, telemedicine integration, can sustain market functionality under conditions of acute physical and institutional disruption, with gross written premiums growing 18.7% to UAH 47 billion in 2024 despite the withdrawal of international reinsurers and the displacement of over eight million civilians. Ukraine's experience establishes that digital investment in insurance delivers not only operational efficiency under normal conditions but institutional survival capacity under extreme ones – a finding with direct relevance for insurance markets in other fragile or conflict-affected contexts.

Prospects for further research follow directly from the gaps identified in this study. Priority should be given to longitudinal assessments of AI's long-term effects on market concentration, competitive dynamics, and the insurability of vulnerable populations: questions that cross-sectional performance studies cannot address. Comparative analyses of AI adoption outcomes across heterogeneous regulatory regimes, particularly between EU-governed markets and emerging economies undergoing post-conflict reconstruction, would generate evidence of direct relevance to international standard-setting bodies.

Empirically grounded evaluation of algorithmic fairness outcomes in production underwriting systems, drawing on regulatory audit data rather than controlled experimental settings, is required to bridge the gap between theoretical bias frameworks and demonstrated real-world discrimination effects.

Research on human capital transitions, specifically the reskilling pathways and organisational role evolution of actuaries and claims professionals in AI-intensive environments, remains fragmented and deserves dedicated interdisciplinary investigation.

Finally, the systemic risk dimensions of widespread AI adoption in insurance, correlated model failures, third-party platform concentration, and adversarial vulnerabilities in shared training infrastructure, represent an emerging research frontier whose policy implications are likely to intensify as deployment scales and regulatory frameworks mature.

Future research may also focus on the development of hybrid analytical frameworks that integrate AI methods with traditional actuarial approaches, as well as on the regulatory and ethical implications of large-scale AI deployment across insurance markets at different stages of institutional development.

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