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INTEGRATION OF INTELLIGENT DIGITAL TECHNOLOGIES INTO ACCOUNTING AND MANAGEMENT SYSTEMS OF INSURANCE COMPANIES

ІНТЕГРАЦІЯ ІНТЕЛЕКТУАЛЬНИХ ЦИФРОВИХ ТЕХНОЛОГІЙ У СИСТЕМУ ОБЛІКУ ТА УПРАВЛІННЯ СТРАХОВИМИ КОМПАНІЯМИ

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Дем'янчук М.А., Маслій Н.Д. Інтеграція інтелектуальних цифрових технологій у систему обліку та управління страховими компаніями. Оглядова стаття.

Зростання обсягів даних та цифровізація страхового сектору роблять традиційні обліково-інформаційні системи (AIS) недостатньо ефективними. Стаття спрямована на дослідження інтеграції Big Data та AI у AIS страхових компаній, оцінку впливу цих технологій на операційну ефективність, прозорість процесів та управлінські рішення. Методологія включає наративний огляд літератури з елементами тематичного аналізу та аналіз практичних кейсів. Результати демонструють, що ML, DL, RPA, Blockchain та GenAI підвищують точність прогнозів, автоматизують рутинні процеси, оптимізують ресурси та персоналізують клієнтський досвід. Висновки підтверджують, що системна інтеграція технологій у поєднанні з розвитком цифрових компетенцій персоналу та дотриманням етичних і регуляторних стандартів формує стійку та конкурентоспроможну екосистему страхового бізнесу.

Ключові слова: Big Data, AI, AIS, страхування, RPA, Blockchain, цифрова трансформація

Demianchuk M.A., Maslii N.D. Integration of Intelligent Digital Technologies into Accounting and Management Systems of Insurance Companies. Review article.

The increasing volume of data and digitalisation of the insurance sector have made traditional accounting information systems (AIS) less effective. This article examines the integration of Big Data and AI into insurance AIS, assessing their impact on operational efficiency, process transparency, and managerial decision-making. The methodology includes a narrative literature review with thematic analysis and practical case studies. Results show that ML, DL, RPA, Blockchain, and GenAI enhance forecasting accuracy, automate routine processes, optimise resources, and personalise customer experience. The study concludes that systematic technology integration combined with workforce digital skill development and adherence to ethical and regulatory standards creates a resilient and competitive insurance ecosystem.

Keywords: Big Data, AI, AIS, insurance, RPA, Blockchain, digital transformation

Modern insurance companies operate with vast volumes of data originating from a wide range of sources, including telematics, IoT devices, financial transactions, social media platforms, and other digital channels [60, 73, 95]. These data are characterised by high update frequency, substantial volume, and structural heterogeneity, which pose significant challenges for traditional accounting information systems (AIS) [87, 136]. Existing systems, primarily designed for conventional accounting operations and financial reporting, are unable to efficiently process such information flows, thereby constraining the potential of predictive analytics, business process automation, and timely managerial decision-making [27, 55].

The ongoing military actions in Ukraine have significantly accelerated the digitalisation of the economy and all spheres of activity, including the insurance industry [27, 55]. In today's context of remote customer service, remote risk assessment, and online management of insurance portfolios, both the speed and scale of data processing have become critical to the effective functioning of insurance companies and all stakeholders in the insurance market [52, 98]. This process underscores the urgency of transforming approaches to accounting and management in insurance companies by adopting modern Big Data processing technologies and artificial intelligence (AI) methods, including explainable artificial intelligence (XAI) models [37, 64].

The integration of Big Data and AI into AIS not only enhances the efficiency of information processing but also enables accurate risk forecasting, optimisation of managerial decisions, automation of routine processes, and improved competitiveness in a rapidly changing economic and regulatory environment [60, 101, 133-134].

The relevance of this study is determined by several key factors. Firstly, the digitalisation of the insurance

business and the rapid growth of data volumes render traditional methods of accounting and management ineffective [87, 136]. Secondly, the development of Big Data and AI technologies opens up new opportunities for optimising financial and managerial accounting, increasing the accuracy of analytical models, and automating routine processes [58, 123]. Thirdly, the integration of these technologies into the practice of insurance companies directly influences their competitiveness, risk management capacity, and compliance with modern regulatory requirements, particularly in relation to personal data processing and cybersecurity [7, 113]. Consequently, data represent a key asset in insurance activities.

Thus, this study aims to analyse the opportunities, advantages, and limitations of implementing Big Data and AI in the functioning of AIS in different types of insurance companies, as well as to assess their impact on the efficiency of managerial and analytical processes.

Analysis of recent research and publications

Theoretical Background and Research Questions.

1. Integration of AI and Big Data in Risk Management.

Recent scholarly work increasingly focuses on the application of AI and Big Data analytics in the fields of risk management, insurance, and financial technologies. There is a clear shift from reactive approaches towards proactive, data-driven decision-making models that combine automation, predictive analytics, and algorithmic transparency [4; 34; 32].

Hierarchical forecasting is considered a key tool for enhancing the accuracy of risk assessment and building resilient business models, particularly in insurance products [34]. Explainable analytical frameworks designed to identify the determinants of accident severity highlight the potential of explainable AI (XAI) in ensuring transparency in risk analytics [4].

2. Technological Synergies: Blockchain, ML and Cybersecurity.

The integration of machine learning (ML) methods with blockchain technologies facilitates more effective fraud detection, reduces transaction costs, and improves the accuracy of forecasts [32]. Decentralised transaction management systems provide new approaches to establishing trust in financial and insurance services [43].

A significant body of recent research is devoted to dynamic risk assessment in real time [32, 34, 77]. The use of telematics data, behavioural models, and predictive analytics enables more precise underwriting and individualised pricing of insurance products, fostering the transition towards personalised insurance models [77].

3. Ethical, Regulatory and Strategic Dimensions.

Considerable emphasis is placed on the ethical and legal dimensions of implementing AI in insurance processes [5; 41]. Issues such as data quality, system scalability, AI integration into legacy infrastructures, and compliance with regulatory requirements, including the GDPR and the AI Act, underscore the necessity of building effective data governance systems [5]. Innovative solutions in cyber insurance are increasingly based on the combination of blockchain and federated learning, strengthening data protection and improving the effectiveness of risk assessment [41].

A synthesis of current scientific approaches demonstrates the growing role of synergies among AI, Big Data, cybersecurity, and regulatory mechanisms in shaping a new architecture of risk management. This reflects the shift from mere technical automation to the construction of resilient, transparent, and data-oriented governance models that form the foundation of the digital transformation of the insurance sector.

4. Research Questions.

The aim of this study is to provide a conceptual synthesis and systematisation of existing knowledge on the integration of Big Data and AI technologies into the AIS of insurance companies. The research is directed at assessing their impact on operational efficiency, transparency, managerial and financial processes, as well as highlighting the practical aspects of their application within the context of the digital transformation of the insurance business. Within this framework, the following research questions are posed:

(RQ1) Which key AI and Big Data technologies and models are integrated into the AIS of insurance companies, and how do they influence efficiency, predictive accuracy, and process transparency?

(RQ2) Which organisational, regulatory, and ethical factors determine the success of implementing these technologies in insurance?

(RQ3) Which practical cases demonstrate the impact of AI and Big Data on risk management, the personalisation of customer experience, and the strategic transformation of business models?

The main part

Research Method.

To achieve the stated aim, this study was conducted in the format of a narrative review [33, 61, 70, 129] with elements of thematic content analysis [39]. This approach was chosen in view of the complex and interdisciplinary nature of the subject matter. A narrative review makes it possible to perform a conceptual synthesis and to establish a theoretical framework for the integration of Big Data and AI technologies into the AIS of insurance businesses, to assess their impact on managerial and financial processes, and to highlight practical aspects of application.

In line with the recommendations of [39, 129], the research process consisted of the following interrelated stages:

(1) Problem formulation and research questions. This stage clearly defined the object, subject, and key questions relating to the integration of Big Data technologies and AI methods into the AIS of insurance companies, as well as the benefits, challenges, and differences in practices between domestic and international insurers (RQ1–RQ3).

(2) Literature search (Search the literature). To ensure the comprehensiveness and relevance of the source base, the search was organised into three

thematic blocks, each corresponding to a "core" category and containing relevant keywords:

(а) data processing technologies: "big data analytics", "artificial intelligence", "machine learning", "robotic process automation", "blockchain";

(б) accounting information systems: "accounting", "ERP", "AIS", "information system";

(в) subject domain: "insurance", "insurance company", "insurance industry".

A source was considered relevant only if it simultaneously fell within all three categories.

To build a comprehensive picture, two types of publications were used:

(2.1) Peer-reviewed academic publications focused on methodology and empirical results, sourced from the Scopus database. Scopus was chosen for its wide coverage of peer-reviewed studies, ensuring reliability and high quality of results [40, 109, 120, 139]. The initial Scopus search was conducted using the Boolean query (1):

TITLE-ABS-KEY (("big data analytics" OR "artificial intelligence" OR "machine learning" OR "robotic process automation" OR blockchain) AND (insurance OR "insurance company" OR "insurance industry")) AND PUBYEAR > 2015 (1)

Further refinement (Refine search) included additional keywords ("accounting" OR ERP OR "information system" OR AIS), restrictions by language (English), availability of full text (All open access) and publication stage "final". The search was completed in September 2025 and covered publications from 2015 to 2025. Based on this combination of criteria, 604 sources were identified in Scopus.

(2.2) Non-peer-reviewed publications were used to complement the academic literature and illustrate the practical context, and included:

— analytical reports and white papers from consulting firms McKinsey [31, 66, 108], Deloitte [49-51], PwC [112], KPMG [84-85, 126], Accenture [2], and BCG [48, 78, 130]; these served as industry benchmarks, combining large datasets, expert evaluations, and strategic forecasts;

— corporate reports on digital transformation from Allianz [8, 10-14, 19, 21], reflecting real-world practices of AI implementation in insurance and providing empirical insights into internal processes, risk management, and telematics products;

— analytical materials from sectoral expertise centres such as Deloitte Center for Financial Services [74, 132] and Swiss Re Risk Knowledge [26, 46, 89-93], combining applied analytics with strategic modelling of market trends;

— professional articles, podcasts, and expert commentaries from McKinsey Podcasts [135] and Allianz MediaCenter [9, 15-18, 20, 54], offering up-to-date industry perspectives, generative AI case applications, and the dynamics of professional discourses;

— Gartner's technological and methodological review [68], providing a practical basis for assessing technology maturity, trends, and ROI scenarios, used as a benchmark dataset for comparison with academic innovation cycle models.

Given the rapid development of Big Data and AI, the timeframe for the publications was restricted to 2020-2025 to ensure topicality.

(3) Evaluate the literature. Following a detailed analysis of full texts and assessment of methodological rigour:

1) out of 604 publications identified in Scopus, 507 were excluded for thematic irrelevance, leaving 97 academic works that met all synthesis criteria;

2) from the non-peer-reviewed corpus, 40 were selected, including 14 analytical reports and consulting white papers, 8 corporate reports, 9 sectoral analytical outputs, 8 professional articles, podcasts and expert commentaries, and 1 technological and methodological review.

(4) Analysis and synthesis of the literature. At this stage, sources were systematised into conceptual blocks: "Impact of Big Data and AI Integration on AIS: Technologies and Methodology"; "Use of Individual Models and Architectures"; "Organisational Changes and AI Implementation Management"; "Impact of AI and Big Data on Operational Efficiency"; "Risk Management and Decision-Making"; "Research Gaps and Emerging Trends".

For a deeper understanding, thematic content analysis was conducted in six phases [39]. Initially, familiarisation with the data involved close reading and note-taking of key ideas and observations (familiarising yourself with your data). Next, initial coding was performed (generating initial codes), identifying significant concepts and patterns reflecting the core aspects of the topic. In the theme-searching phase (searching for themes), codes were grouped into potential themes based on conceptual affinity, followed by reviewing themes to refine their boundaries and ensure consistency with the data. The defining and naming phase (defining and naming themes) provided each theme with a precise definition and consistent label. Finally, findings were presented analytically (producing the report) as a coherent narrative integrating conceptual blocks and highlighting the link between theoretical insights and practical relevance. This approach ensured systematicity, transparency of analysis, and a reliable foundation for interpreting the results.

(5) Present the findings. The results were presented as a logically connected narrative that integrates conceptual blocks, thematic patterns, and practical illustrations, thus providing a comprehensive reflection of the research problem.

Results and discussion.

The review of the selected publications highlights their interdisciplinary character, as research on the integration of Big Data and AI into AIS in the insurance sector has been actively developing at the intersection of several academic and applied fields [87, 136]. The most prominent disciplinary domains include accounting, insurance, data science, information systems, and risk management [60].

The methodological spectrum of the analysed studies is highly diverse, comprising systematic literature reviews [27, 55], bibliometric analyses, empirical case studies, algorithmic benchmarking [22], and governance framework analysis [52]. This diversity reflects the complexity of the topic and the necessity of multidimensional approaches.

The consolidated review allows several key trends to be identified:

1. Big Data and AI in the insurance sector are increasingly viewed not only as instruments for enhancing operational efficiency but also as drivers of strategic transformation of business models [87].

2. Within AIS, the role of intelligent technologies in both financial and managerial accounting is expanding – from transaction processing automation and enhanced transparency of financial reporting to the integration of analytics for managerial decision-making [136].

3. The studies emphasise the dual nature of these processes: while creating new opportunities for improving the accuracy, speed, and flexibility of accountting operations, they also generate challenges linked to ethical, regulatory, and organisational aspects [52, 60].

Taken together, the reviewed publications capture both the theoretical foundations and the practical dimensions of the transformation of insurance companies under the influence of Big Data and AI.

4.1. Impact of Big Data and AI Integration on AIS: Technologies and Methodology

Modern information systems of insurance companies are increasingly integrating advanced technologies that enable a new level of automation and analytical support for managerial processes [59, 73]. The key directions include:

— analytical technologies of machine learning (ML) and deep learning (DL) [22, 42];
— robotic process automation (RPA) [142];
— transaction transparency through blockchain [99, 111].

ML and DL form the analytical core of information systems, ensuring more accurate analysis of large datasets and the identification of patterns [27, 95]. ML enhances the quality of risk assessment and the accuracy of claims forecasting [52], while DL processes complex data types (images, text) [22], enabling automated loss assessment and faster claims settlement.

RPA automates routine back-office processes, reduces staff workload, and shortens data-processing times [142, 137]. Blockchain ensures transparency and immutability of records, data verification, and smart contract execution [63, 99, 116], which is particularly valuable for multi-party agreements and regulatory compliance monitoring [23, 76]. Specific emphasis is placed on the potential of blockchain-based solutions to improve financial security in insurance and healthcare [24, 67], as well as the use of decentralised models to counter price discrimination and audit transactions [102]. A notable direction is the integration of Hyperledger into medical and insurance information systems, demonstrating the feasibility of scalable and secure data storage [96].

Methodologically, integration is most frequently structured using the CRISP-DM approach, which encompasses the entire cycle from defining the business problem to implementing analytical solutions [137]. Its robustness is supported by the use of mixed methods (systematic review, case studies, expert interviews) [55, 60].

The combination of technologies creates a cumulative effect: (a) analytics (ML, DL) improves forecasting accuracy and financial reporting [73]; (b) RPA automates routine processes, ensuring speed and scalability [142]; (c) blockchain guarantees transparency and regulatory compliance [98, 107]. A detailed application of these technologies across different CRISP-DM stages is presented in Table 1.

Table 1. Application of ML, DL, RPA and Blockchain in Insurance AIS Based on CRISP-DM and Mixed Methods

Technology	Application examples	Synergy	Insights from reports
1	2	3	4
CRISP-DM: Business Understanding			
ML	Forecasting key business risks and needs; supporting pricing	ML + Blockchain = precise risk assessment with transparent transaction validation	McKinsey: underwriting cost reduction 20-30 % [108]; SwissRe: catastrophe risk accuracy+10-15 % [26]
DL	Analysis of complex claims cases; trend modelling		
RPA	Identification of repetitive processes for automation		
Blockchain	Defining processes requiring transparency and transaction security		
CRISP-DM: Data Understanding			
ML	Identifying patterns in client and policy data	DL + Blockchain = verification of visual/textual evidence with guaranteed validity	Gartner: XAI as a key to transparency [68]; Deloitte: Responsible AI as the foundation of ethics and trust [50]
DL	Analysis of images, videos, and textual descriptions of claims		
RPA	Verification of data sources for automated processing		
Blockchain	Data verification among market participants		
CRISP-DM: Data Preparation			
ML	Data cleansing, normalisation, integration for modelling	ML + RPA = standardisation of large datasets	PwC: data preparation automation reduces operating costs by 20-25 % [112]
DL	Preparing complex unstructured data (images, sensors, text)		
RPA	Automating data transformation into standardised formats, ERP/CRM integration		
Blockchain	Structuring transaction records		

Continuation of Table 1

1	2	3	4
CRISP-DM: Modelling			
ML	Developing predictive models for risk and pricing	ML + DL = more accurate risk models; DL + RPA = automated claims assessment	Accenture: "AI-first insurers" – up to 90 % of processes supported by AI analytics [2]
DL	Detecting anomalies in claims; automated damage assessment		
RPA	Automated form filling and premium calculation		
Blockchain	Using smart contracts in insurance agreements		
CRISP-DM: Evaluation			
ML	Validating risk models	Blockchain + ML = transparent audit of models	Deloitte: independent audit of AI models as a regulatory requirement [51]
DL	Verifying DL algorithm performance		
RPA	Monitoring the correctness of automated processes		
Blockchain	Auditing and validating transactions		
CRISP-DM: Deployment			
ML	Implementing predictive models into workflows	RPA + Blockchain = omated transactions and reporting with guaranteed transparency	PwC: claims processing time reduced from weeks to hours [112]; BCG: ROI from AI in financial processes15-35 % [130]
DL	Integrating neural networks into AIS		
RPA	Automating claims handling and document verification		
Blockchain	Reporting and smart contract execution		

Source: elaborated by the authors based on [2, 26, 50-51, 68, 108, 112, 130]

Thus, the modern architecture of AIS in insurance companies presupposes a systemic integration of ML, DL, RPA, and blockchain within CRISP-DM [59, 123]. This ensures comprehensive process support: from enhancing the accuracy of financial reporting and actuarial calculations to automating daily operations and ensuring transaction transparency [58, 72].

According to reports by McKinsey [108], Deloitte [49], PwC [112], and SwissRe [26, 89-93], the integration of Big Data and AI in insurance has a particularly strong impact on:

1. Underwriting and pricing – automation reduces underwriting costs by 20-30 % [108] and improves catastrophe risk forecasting accuracy by 10-15 % [90].

2. Transparency and trust – the adoption of XAI and Responsible AI narrows the "trust gap" and ensures regulatory compliance [49, 68].

3. Customer service and claims automation – claims settlement is shortened from weeks to hours [112], while "AI-first insurers" models support up to 90% of operational activities through AI-driven analytics [2].

In summary, the analytical integration of results indicates that the adoption of Big Data and AI in insurance is multidimensional: it simultaneously enhances operational efficiency and transparency [69, 99], reduces costs and accelerates processes [78], but also requires due attention to ethical and workforce-related aspects [27, 60]. Thus, the digital transformation of insurance AIS can be considered a strategic factor in their competitiveness [59].

2. Use of Individual Models and Architectures.

In contemporary insurance, individual AI models are integrated into AIS to enhance forecasting accuracy, data-processing speed, and business-process transparency (Table 2) [6, 30, 36, 65]. The most prevalent application is DL, where convolutional neural network (CNN) architectures (ResNet50, InceptionV3, EfficientNet) are employed for automated loss assessment and image processing [44, 133-134, 140]. According to Swiss Re (2024) [80, 93], the use of CNN combined with satellite imagery analysis for catastrophic risks reduces claims-assessment time by 30-40 %, indicating a substantial efficiency improvement compared to traditional expert-based evaluations.

Tabular-data models (TabNet, LightGBM, XGBoost) demonstrate high efficiency in telematics insurance, risk scoring, and client segmentation, increasing risk-forecast accuracy by 20-40 % and reducing insurance-reserve estimation errors by 15-25% [30, 65, 83, 108, 128]. These algorithms enable a balance between calculation accuracy and speed in underwriting and financial forecasting [82, 112].

An important development area is XAI (SHAP, Feature Importance), which enhances decision-making transparency in risk management and complies with regulatory requirements [37, 50, 68, 101]. Its integration fosters greater trust in algorithmic assessments and supports high-quality managerial and regulatory reporting.

RPA platforms (UiPath, Automation Anywhere, Blue Prism) automate routine operations – from premium accounting and report preparation to document verification [25, 62]. Deloitte [51] predicts this can reduce costs by 20-40 % and accelerate operational cycles by 30-50 %, which, when combined with ML and DL models, enables comprehensive process optimisation [29, 57].

Blockchain is integrated to ensure transaction transparency and smart-contract execution, particularly in microinsurance and regulatory auditing [79, 112]. Its implementation can reduce transaction-verification time from days to minutes [20, 112], increasing market participants' trust and improving the quality of regulatory reporting [28, 81].

Overall, the combination of ML, DL, RPA, and blockchain creates an integrated ecosystem for the digital transformation of insurance AIS: ML and DL provide enhanced risk-forecast accuracy [75, 44], RPA reduces costs and accelerates cycles [2], and blockchain ensures transparency and trust in interactions with clients and regulators [19, 79]. Thus, the deployment of these technologies generates operational benefits while reinforcing the strategic position of insurers in the digital economy [46, 78, 130].

Table 2. Application of Advanced Technologies in Insurance AIS: Models, Methodology, and Use

Technology	Model / Architecture	Practical Application	CRISP-DM Stages	Insights from Reports
ML	XGBoost	Premium forecasting, risk assessment [115, 143]	Business Understanding, Modeling, Evaluation	Most effective for telematics insurance and risk scoring [130]
	Random Forest	Fraud detection, risk classification [45, 47]	Data Understanding, Modeling	
	LightGBM	Telematics claims, client segmentation [30, 118, 141]	Modeling, Evaluation	
	Logistic Regression	Underwriting decision-making [97, 106, 110]	Modeling, Evaluation	
DL	CNN (ResNet50, InceptionV3, EfficientNet)	Vehicle-loss verification, fraud detection [93]	Data Preparation, Modeling	Swiss Re uses CNN for satellite imagery analysis in catastrophic risks [93]
	TabNet	Telematics claims, underwriting [6; 64]	Data Understanding, Modeling	
	Transfer Learning	Actuarial calculations, loss forecasting [53, 140, 146]	Modeling, Deployment	
Hybrid / XAI	Fuzzy Logic + ML	Portfolio profitability forecasting [93]	Modeling, Evaluation	Combines traditional actuarial methodology with ML in reinsurance [93]
	SHAP, Feature Importance	Underwriting, risk assessment [37, 100, 133]	Evaluation, Deployment	
RPA	UiPath, Automation Anywhere, Blue Prism	Claims processing, policy updates, document verification, CRM/ERP integration [2, 51]	Data Preparation, Deployment	By 2025, over 50 % of insurers plan to automate accounting operations [51]
Blockchain	Ethereum / Hyperledger	Automated compensation, policy auditing, inter-insurer transactions [8-9, 71, 79, 112, 124]	Deployment, Evaluation	Smart contracts applied in microinsurance for automated settlements [112]; increase regulatory reporting transparency [8-9]

Source: elaborated by the authors based on [2, 6, 8-9, 30, 37, 45, 47, 51, 53, 64, 71, 79, 93, 97, 100, 106, 110, 112, 115, 118, 124, 130, 133, 140-141, 143, 146]

3. Organisational Changes and AI Implementation Management.

Successful AI implementation in insurance companies primarily depends on effective management of organisational changes, encompassing leadership, communication, and staff competence development (Table 3). According to studies [78, 108, 119, 130, 136], only 10-20% of companies achieve significant business impact from scaling AI without systematic change management. Key success factors include executive support, transparency of information flows, investment in employee training, and the use of innovative change-management platforms [38, 56, 113].

Table 3. Key Aspects of Organisational Changes and AI Implementation Management in Insurance Companies

Category	Key aspects	Practical examples / Tools	Expected effect
Leadership and top management support	Active executive involvement, strategic planning	Executives set priorities and provide resource backing	Enhanced organisational readiness, reduced employee resistance [78, 108, 130]
Transparent communication	Systematic staff briefings on changes	Explaining AI benefits, demonstrating process impact	Reduced resistance, increased trust, more effective implementation [7, 68]
Employee upskilling	Targeted training, continuous education	Courses on AI, ML, Big Data, practical automation cases	Closing the digital gap, skill development, reduced change-related anxiety [113, 136]
AI-oriented change-management platforms	Automation and personalisation of processes	Platforms for training, support, and implementation planning	Faster technology adoption, increased employee engagement [51, 112, 145]
AI analytics: telematics and geospatial analysis	Using data for risk assessment	GPS, sensor data, geospatial datasets	Personalised products, dynamic pricing, improved underwriting [15-16, 46]
Customer orientation and ethical aspects	Product personalisation, compliance with ethics and privacy	AI analytics, privacy policies, GDPR/AI Act	Increased customer satisfaction, regulatory compliance [3, 56, 83, 125]

Source: elaborated by the authors based on [3, 7, 15-16, 46, 51, 56, 68, 78, 83, 108, 112, 113, 125, 130, 136, 145]

Leadership plays a pivotal role: top management not only defines strategy but also shapes a culture open to innovation, creating conditions for aligning digital transformations with long-term company objectives [38, 113]. Transparent communication reduces employee resistance by providing a clear explanation of technology benefits and expected outcomes [7, 86].

Upskilling programs are particularly critical. According to the PwC AI Business Survey [112], over 60% of companies invest in retraining employees in analytics, ML, and automation, reducing the digital gap and accelerating staff adaptation to new operational conditions. The use of AI-oriented change-management platforms personalises educational processes and integrates them into daily company activities [38, 51], enhancing engagement and sustaining transformation outcomes.

Ethical and regulatory considerations are also essential. Forecasts [68] indicate that over 70% of companies will implement ethical AI frameworks by 2026 to prevent discrimination, ensure confidentiality, and mitigate regulatory and reputational risks [105, 125].

Thus, organisational changes in AI implementation within insurance go beyond technical aspects. They encompass strategic leadership, digital competence development, and the establishment of an ethical infrastructure [56, 122]. Integrating these components enhances business-process efficiency, reduces risks, and ensures trust from both clients and regulators [119, 136].

4. Impact of AI and Big Data on Operational Efficiency.

The integration of advanced AI technologies and Big Data analytics into insurance AIS is radically transforming companies' operational efficiency (Table 4). A primary focus is process automation. The use of RPA in combination with AI minimises human involvement in routine accounting, auditing, and operational tasks [88, 138].

According to McKinsey [108], back-office process automation with AI and RPA reduces processing time for claims by 30-50% and decreases financial transaction costs by 30-40%. RPA platforms effectively integrate with CRM/ERP systems, automating premium, reserve, and payout accounting, as well as regulatory reporting [127]. AI analytics and ML models (XGBoost, LightGBM, CNN, TabNet, Transfer Learning) enhance the accuracy of insurance reserve estimation (reducing errors by 15-25 %) and improve predictive accuracy by 20-40 % [46, 50, 144].

Table 4. Directions for Improving Operational Efficiency of Insurance AIS via AI and Big Data

Efficiency Focus	Methods and Technologies (examples)	Practical Application	Key Results / Effects
Process automation	RPA and AI for routine task automation (UiPath, Automation Anywhere, Blue Prism)	Automation of accounting and auditing tasks, claims processing, policy updates	Reduced human error, freed resources for strategic tasks and optimisation [103]
Accuracy of financial reporting and analytics	Predictive analytics and ML models (XGBoost, LightGBM, CNN, TabNet, Transfer Learning)	Improved accuracy and timeliness of reports, data-driven auditing, risk forecasting, pricing, claims assessment	Enhanced audit quality, reduced information asymmetry, fewer risk assessment errors, improved forecast accuracy [1; 35]
Resource and workload optimisation	AI analytics and automated task allocation (AI-CRM, ML models)	Staff workload management, resource planning	Significant time reduction, higher productivity, reduced staffing needs [103; 144]
Customer service quality and personalisation	AI analytics for personalisation and dynamic pricing (AI-CRM, telematics, behavioural analytics)	Tailored offers, dynamic insurance, client recommendations	Increased customer satisfaction, loyalty, and retention [83; 94; 117]
Transparency and compliance	Analytics and Blockchain (Ethereum, Hyperledger)	Audit of financial and insurance transactions, regulatory compliance	Reduced fraud risk, compliance assurance, enhanced trust [121; 131]

Source: elaborated by the authors based on [1, 35, 83, 94, 103, 117, 121, 131, 144]

Resource optimisation and workload management are enabled through AI analytics and intelligent workflow management systems. ML models and generative AI (GenAI) allow tasks to be allocated efficiently, reducing processing time by 25-50 % and increasing productivity by 20-30 % [2, 8-9, 15-21, 104]. In practice, a single employee supported by AI can accomplish work previously requiring 15-18 staff [103].

Customer personalisation and experience are realised through the combination of AI analytics, telematics, behavioural analysis, and client-oriented AI-CRM/GenAI systems. This enables customised insurance products, real-time recommendations, and automated client interactions. Case studies demonstrate that AI-driven personalisation increases customer satisfaction by 15-25%, raises Net Promoter Score by 36 points, and reduces complaints by 65% [108, 147].

Transparency and regulatory compliance are ensured through integrated analytics and Blockchain platforms (Hyperledger, Ethereum). These technologies enable automated transaction auditing, reduce verification time from days to minutes, and decrease fraud risk by 15-25% [51, 18-21, 114].

Strategic leadership and change management play a key role in AI and Big Data adoption: executive support, transparent communication, and systematic staff training foster an innovation culture and ensure effective technology integration [50, 78, 88, 130].

For clarity, Table 5 summarises typical KPIs and practical effects of integrating Big Data, AI, RPA, and GenAI into insurance AIS.

Table 5. Key Performance Indicators for Optimising Insurance Processes

Efficiency Focus	Technologies	Typical KPI (benchmark)
Process automation / Back-office efficiency	RPA, ML, GenAI	30-50% reduction in claims processing time [108]
	RPA, AI-based workflow automation	20-40% reduction in back-office costs [51]
	RPA	40-50% automation of routine tasks [92]
	NLP, GenAI, DL, Conversational AI	25-30% productivity increase in call centres [20]
	RPA, AI-CRM	40% reduction in claims processing time [92]
	AI for Transactions	80% of transactions automated online [108]
	ML, DL	15-35% ROI from AI in financial processes [130]
Accuracy and Predictive Analytics	ML, DL (XGBoost, CNN)	20-40% improvement in risk forecast accuracy [31]
	ML, Predictive Analytics	15-25% reduction in reserve estimation errors [46]
	ML, GenAI	20-30% improvement in audit and analytics reporting [49]
	GenAI, Finance AI	30-50% reduction in risk assessment time [108]
	ML	+1,5-3 pp improvement in technical results [108]
	ML	1,5-3% premium growth [108]
	Blockchain, AI-based validation	Reduced information asymmetry and human error in accounting [16]
Resource optimisation / Workforce efficiency	RPA, AI-CRM, ML	25-50% reduction in task processing time [2]
	ML-driven workforce analytics, GenAI, Workforce AI	20-30% productivity increase through AI automation [18]
	ML, AI resource allocation	15-20% optimisation of staff without productivity loss [93]
	GenAI, AI Adoption	100% increase in employee engagement [108]
	Enterprise AI	90% of employees using AI (50 % daily) [20]
Customer service quality and personalisation	ML, GenAI	15-25% increase in customer satisfaction via AI personalisation [66]
	GenAI, Customer AI	+36 points in NPS [108]
	GenAI	65% reduction in customer complaints [66]
	GenAI, Contact Center AI	3-minute reduction in call duration [51]
	AI-CRM, ML personalisation	10-20 % increase in loyalty and retention [50]
	NLP, RPA	30 % reduction in customer query response time [19]
Transparency and compliance	Blockchain, RPA	Transaction verification time reduced from days to minutes [51]
	Blockchain	Increased accuracy of financial recording and regulatory compliance [89-90]
	ML anomaly detection, Blockchain	15-25% reduction in fraud risk [15]
	AI for Reinsurance	Reduced decision time in reinsurance [46]

Source: elaborated by the authors based on [2, 15-16, 18-20, 31, 46, 49-51, 66, 89-90, 92-93, 108, 130]

In summary, the combination of AI and Big Data in insurance AIS generates a synergistic effect [1, 117, 144]: process automation, improved accuracy of financial reporting and risk forecasts, resource optimisation, personalised client experience, and transaction transparency. Collectively, these factors create a resilient and competitive operational ecosystem.

5. Risk Management and Decision-Making.

The integration of AI and Big Data analytics fundamentally transforms risk management approaches and decision-making processes in insurance. These technologies enable proactive identification of emerging threats, support risk management strategies, and contribute to resilient business models [34].

One of the most prominent applications of AI and Big Data in risk management is fraud detection. ML algorithms can process large volumes of transactional and behavioural data, identifying anomalous patterns indicative of potential fraud [4, 32]. This reduces financial losses and accelerates decision-making in risk management.

Dynamic real-time risk assessment is another critical element. Predictive analytics and ML models improve underwriting accuracy and ensure fair pricing, enhancing the resilience of insurance portfolios [43]. Behavioural models and telematics data are increasingly important, allowing individual client characteristics (driving style, lifestyle, financial behaviour) to be incorporated into risk management processes [77, 83]. This enables proactive risk assessment and personalised insurance products.

Regulatory and technological aspects also require attention. Challenges include data quality, system scalability, and integration of AI solutions into legacy infrastructure. Addressing these requires modern IT infrastructure, robust data governance, and compliance with GDPR and AI Act [5].

In cyber insurance, AI demonstrates particular effectiveness. Platforms such as Cyber Risk Intelligence Platform combine ML, NLP, federated learning, and Blockchain to monitor threats in real time, improving risk assessment accuracy and data protection [41]. Reinforcement learning and predictive analytics enable dynamic pricing, adapting premiums to changing risk environments. Integrating AI with Blockchain supports automated claims settlement and improves fraud detection accuracy – in some cases up to 98% [5, 32].

The integration of technological, regulatory, and strategic components of risk management in insurance AIS is illustrated in Figure 1.

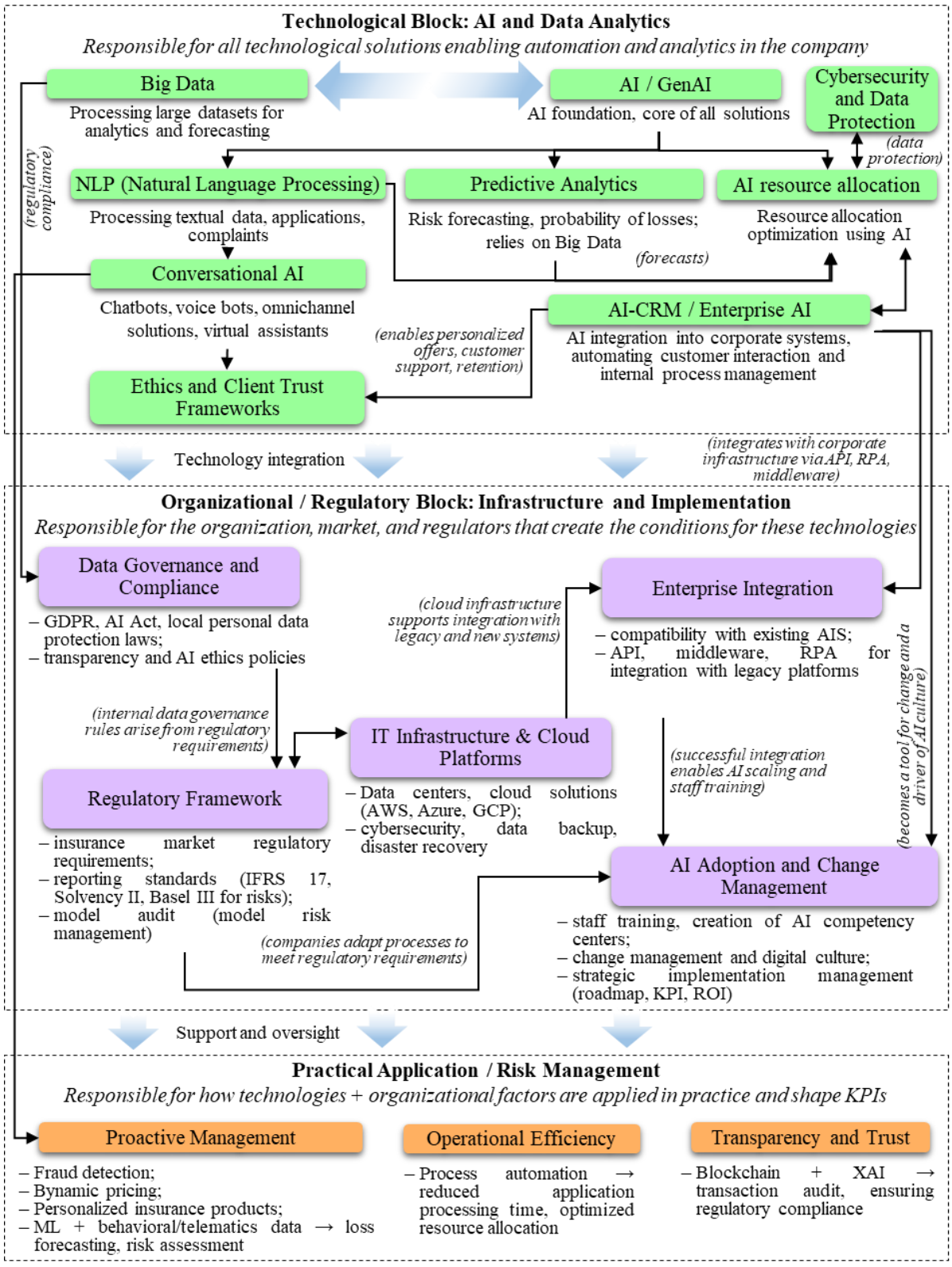

Figure 1. Integrated Model of Risk Management and Decision-Making Based on AI and Big Data in Insurance AIS
Source: authors' own elaboration

The model demonstrates how the interaction between Big Data, AI/GenAI, and enabling components (cybersecurity, ethical frameworks, client trust management) forms a comprehensive risk management architecture. The top layer represents the technological-analytical foundation – NLP, predictive analytics, AI-driven resource allocation, and integrated AI-CRM systems – enabling real-time data collection, processing, and interpretation. The middle layer illustrates the organisational-regulatory environment – Data Governance, Compliance, Enterprise Integration, Regulatory Framework, and AI Adoption and Change

Management – ensuring legal compliance and technological interoperability. The bottom layer represents integration outcomes – proactive management, operational efficiency, transparency, and trust, which are key indicators of digital insurance maturity.

The model reflects the transition from traditional, reactive approaches to data-driven, dynamic risk management, where AI and Big Data form the core of decision-making processes, and ethical and regulatory elements ensure resilience and legitimacy in the digital ecosystem.

Thus, AI and Big Data establish a new paradigm for risk management and operational efficiency in insurance. They enable the shift from reactive models to proactive, data-driven strategies, improving forecast accuracy, optimising resources, and reducing financial losses. Integration of these technologies simultaneously enhances client and regulator trust while strengthening company competitiveness.

6. Research Gaps and Emerging Trends.

Despite significant progress in implementing AI and Big Data in insurance AIS, notable research gaps remain. A key issue is the limited number of empirical studies capable of quantifying the impact of AI and Big Data on insurance company performance across different regulatory environments. Furthermore, the human factor remains underexplored: how change management, reskilling, and psychological adaptation of personnel influence the success of digital transformation. An important direction is the development of transparent, standardised, yet sufficiently flexible AI governance systems that combine innovation with accountability.

One of the most debated issues is algorithmic bias, which can lead to systematic errors and client discrimination. Addressing algorithmic bias requires both technical solutions (XAI, stress-testing models) and legal mechanisms to ensure fairness and non-discrimination. Large-scale use of client data heightens the need for compliance with regulatory acts (GDPR, AI Act), but unified models for their application in insurance are still lacking.

In response to these challenges, new approaches to AI governance are being developed. Promising directions include the advancement of XAI to enhance trust, multi-level governance models (regulations + standards + certification), and ethical frameworks based on fairness and non-discrimination principles.

A critical challenge remains integrating workforce competency development (digital literacy, analytical skills, critical thinking) with strategic leadership in technology adoption. In the future, the role of AI operational auditing – analogous to financial auditing – is expected to grow, allowing systematic evaluation of models for bias and ethical compliance. Global trends and projections include productivity gains from GenAI (+0,1-0,6 % GDP per year by 2040), an economic impact of $ 4.4 trillion annually [108], expansion of the insurance market to $ 8 trillion in premiums [51], and the growing role of AI-first business models [2, 78, 130].

Thus, addressing research gaps – in measuring AI impact, managing the human factor, establishing transparent governance mechanisms, and developing ethical practices – requires interdisciplinary collaboration. Only through such collaboration can a resilient and socially responsible insurance ecosystem be created in the context of digital transformation.

Conclusions

The integration of Big Data and AI technologies into insurance AIS represents a core component of digital transformation in the insurance industry. These technologies enhance accounting accuracy, transparency of management processes, resource optimisation, and accelerate both strategic and operational decision-making. The study provides a comprehensive overview of technological, organisational, and practical aspects of this integration, addressing three main research questions.

The study demonstrates that key AI and Big Data technologies and models (ML, DL, RPA, Blockchain, GenAI) are integrated into modern AIS across different CRISP-DM stages, producing a synergistic effect (RQ1): automation of routine processes, improved forecast and financial reporting accuracy, transaction transparency, and resource optimisation. Advanced models such as CNN, TabNet, XGBoost, and SHAP enable effective risk assessment, personalised insurance products, and reduction of processing times by 30-50%.

Organisational, regulatory, and ethical factors determine the success of technology implementation (RQ2). Top-management leadership, transparent communication, workforce digital skill development, and AI-oriented change management platforms are critical for effective integration. Ethical and regulatory frameworks, such as GDPR and AI Act, reduce risks of discrimination, privacy violations, and non-compliance.

Practical cases demonstrate the significant impact of AI and Big Data on risk management, customer experience personalisation, and strategic business model transformation (RQ3). ML algorithms and AI analytics enable proactive fraud detection, risk forecasting, and resource optimisation. RPA and GenAI reduce costs and increase employee productivity, while Blockchain ensures transaction transparency and regulatory compliance. KPIs for technology integration include reducing processing times by 30-50%, improving forecast accuracy by 20-40%, lowering financial reporting errors by 15-25%, and increasing customer satisfaction by 15-25%.

Overall, the findings indicate that integrating Big Data and AI into insurance AIS creates a synergistic ecosystem that simultaneously enhances operational efficiency, transparency, forecast accuracy, and strategic flexibility. At the same time, it requires a systematic approach to change management, workforce competency development, and adherence to ethical and regulatory standards. The novelty of this article lies in the detailed mapping of advanced AI and Big Data technologies and models across various AIS stages in insurance companies and in evaluating their impact on operational efficiency, process transparency, and management decision quality.

Abstract

In the context of the digitalisation of the insurance sector and the significant growth of data volumes, traditional accounting information systems (AIS) prove to be insufficiently effective for risk management, loss forecasting, and support of strategic decision-making. The aim of this study is to provide a conceptual synthesis and systematisation of existing knowledge on the integration of Big Data and AI technologies into the AIS of insurance companies. Within this framework, the following research questions are posed: (RQ1) Which key AI and Big Data technologies and models are integrated into the AIS of insurance companies, and how do they influence efficiency, predictive accuracy, and process transparency? (RQ2) Which organisational, regulatory, and ethical factors determine the success of implementing these technologies in insurance? (RQ3) Which practical cases demonstrate the impact of AI and Big Data on risk management, the personalisation of customer experience, and the strategic transformation of business models?

This study was conducted in the format of a narrative review with elements of thematic content analysis, which allows the systematisation of existing publications, assessment of the practical impact of technologies on insurance processes, and identification of key organisational, regulatory, and ethical factors. Analysis covers Peer-reviewed academic publications focused on methodology and empirical results, as well as Non-peer-reviewed publications were used to complement the academic literature and illustrate the practical context (analytical reports and white papers from consulting firms, corporate reports on digital transformation, analytical materials from sectoral expertise centres, professional articles, podcasts, and expert commentaries, technological and methodological review). Given the rapid development of Big Data and AI, the timeframe for the publications was restricted to 2015-2025 to ensure topicality for Peer-reviewed academic publications and 2020-2025 to ensure topicality for Non-peer-reviewed publications.

Sources were systematised into conceptual blocks: "Impact of Big Data and AI Integration on AIS: Technologies and Methodology"; "Use of Individual Models and Architectures"; "Organisational Changes and AI Implementation Management"; "Impact of AI and Big Data on Operational Efficiency"; "Risk Management and Decision-Making"; "Research Gaps and Emerging Trends". They demonstrate that the integration of ML, DL, RPA, Blockchain, and GenAI increases the accuracy of forecasts and financial reporting, automates routine processes, optimises resources, and personalises insurance products. Organisational and regulatory factors, including top-management leadership, development of employees' digital competencies, transparent communication, and compliance with ethical and legal standards (GDPR, AI Act), determine the success of technology implementation.

The findings indicate that integrating Big Data and AI into insurance AIS creates a synergistic ecosystem that simultaneously enhances operational efficiency, transparency, forecast accuracy, and strategic flexibility. At the same time, it requires a systematic approach to change management, workforce competency development, and adherence to ethical and regulatory standards. The novelty of this article lies in the detailed mapping of advanced AI and Big Data technologies and models across various AIS stages in insurance companies and in evaluating their impact on operational efficiency, process transparency, and management decision quality.

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