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Public Property Insurance Systems in EU Countries and Possibilities for Using AI in Insurance

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Abstract: *This paper presents an analytical synthesis of current approaches to public property insurance in an international context. The aim is to identify the approaches of individual EU countries to the issue of protecting public property and propose a general model for the use of AI in this area. The analysis is carried out in the form of research, based on a methodology of systematic collection, sorting and evaluation of primary and secondary sources. The main sources include scientific publications and government documents. Emphasis is placed on categorising the identified approaches of countries in this area and the possibilities of using AI in the insurance industry. This article enriches the scientific and research space with a unique overview of the approaches of individual EU countries, which is currently lacking. The results of the study can serve as a starting point for further studies and a valuable resource for deepening knowledge in this area. Since the use of AI has not been confirmed in most countries and the individual approaches in EU countries show only slight differences, the proposed general model can be applied at individual national levels of public institutions in EU countries.*

Keywords: *public property, insurance, public administration, artificial intelligence*

JEL: *H83, G22, H82*

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Introduction

In an environment of global challenges, changes and artificial intelligence (AI) transformations, the issue of effective insurance of public property is of fundamental importance for the sustainability of public finances. It also has synergistic significance in terms of the state's resilience to increasingly frequent crisis situations, threats and various other unpredictable events.

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Public property represents the basic infrastructure for the provision of public services, the fulfilment of the state's legal obligations and the maintenance of social stability (Fedchenko et al. 2023, Kattel et al., 2023, Manganelli et al., 2022). Its protection is essential for the resilience and functionality of the public sector. However, not all forms of public property necessarily require protection through insurance coverage. The paradigm shift in public property insurance is relatively new. It is based on the premise that public property insurance should be a risk management tool, not an automatic solution for all types of property (Giraldez-Puig et al., 2024, Addison & Halbert, 2022). In the context of the increasing frequency of extreme weather events, technological threats and geopolitical uncertainties, states are increasingly focusing on strategic risk assessment and the effective allocation of resources (Kunikowski & Kisilowski, 2022). From an economic point of view, blanket insurance is considered unjustified. Approaching insurance regardless of the nature of the property or its strategic importance is unsustainable, harmful and contrary to modern risk management principles. The trend of applying selective insurance of public property is gradually being adopted by all European Union (EU) states, confirming and consolidating a new paradigm in risk management and public property protection. A targeted approach to the protection of public property allows states to optimise their expenditure on its protection, which is in line with the principles of good governance and financial discipline.
However, the change in approach to public property insurance is not the only sign of transformation in the insurance environment. Another fundamental driver is the rise of digital technologies, particularly AI, which opens up new possibilities in the field of risk management (Bhattacharya et al., 2025, Dvorsky, 2025, Figura & Vevere, 2025, Amerirad et al., 2023, European Commission, 2020, Corea, 2019). Today, AI enables government institutions and insurance companies to work with large amounts of data, identify threat patterns, predict the development of risk factors, and propose flexible insurance strategies (Gramegna & Guidici, 2020). Thanks to these capabilities, AI is becoming a key tool in deciding what to insure (Vesolovska et al., 2025), how to set coverage, and where costs are commensurate with expected benefits (Grize et al. 2020, Maalla, 2021). Combined with a rational selection of insured assets, this creates a new model for protecting public property that is not only more effective but also better adapted to the dynamics of today's risk environment.
This paper focuses on analysing approaches to public property insurance in selected EU states. The authors emphasise the identification of tools and system of insurance. At the same time, they seek to fill a gap that has been identified in this area and offer a starting point for further research and professional discussion. In addition, they focus their efforts on developing a model that can be flexibly adapted to the conditions of individual countries and public institutions, enabling its practical implementation across diverse public administration environments.
Methodologically, the study is based on a systematic review of secondary sources, including scientific publications, legislation, official documents of public institutions, strategic materials, reports of international organisations and analytical outputs of professional institutions.

1. Insurance of public property

Public property represents the basic infrastructure of public life. It consists of buildings of state institutions, means of transport, technological equipment, cultural and historical monuments, and the like. The protection of public property is not only a matter of economy, but also of strategic risk management. These risks can threaten the continuity of public services, the safety of the population, and the stability of public finances.

In the context of growing environmental threats, technological incidents and geopolitical uncertainties, public property insurance is becoming an integral part of a comprehensive system of responsible management of public resources. In this context, insurance takes on two dimensions, namely a social dimension and an economic dimension (Shabani, 2022).

Insurance of public property is a specific form of strategic risk management in the public sector. It is the subject of strategic decision-making that requires a comprehensive assessment of risks, property value and impacts on public finances.

The essence of public property insurance is to protect public assets from unforeseen events that could have a significant impact on the continuity of public services, the stability of public finances and the overall quality of life of the population. It reduces the economic burden on the state, helps to speed up recovery, minimises economic losses and enables more effective management of financial costs and reduces the burden on the state budget (Financial Protection Forum, 2020).

Insurance principles, such as the necessity of insurable interest, compensation for actual damage, information balance and cooperation in damage reduction (Montero et al., 2023, Kratenko & Luik, 2020), apply in the case of public property in the context of its public nature and legal framework of administration. In the case of the state and its property, the insurance mechanism is seen as a preventive tool that allows the state to systematically approach the protection of its property.

Insurance claims relating to public property are dealt with under specific insurance contracts that cover the risk of damage to or destruction of public property. The state can be insured against various risks, such as natural disasters, terrorism, damage or theft. However, in the case of a special owner such as the state, its obligation to protect the property entrusted to it must be taken into account (Act 278/ 1993 Z. z. on the management of public property in Slovak republic).

The state also has a duty to protect entrusted property in cases closely linked to climate change. Climate change significantly increases the frequency and severity of natural disasters, which puts growing pressure on insurance markets in the EU. Messina and Prowse (2025), EIOPA (2024), and the ECB (2023) point out that new climatic conditions are changing the nature of risks to such an extent that traditional insurance models are no longer sufficient and many regions may become uninsurable. The response to this reality is the EU's new climate change adaptation strategy, which emphasizes that the affordability and availability of insurance coverage for natural disasters is likely to become an increasingly serious problem not only for households and businesses, but also for public institutions. In response to this problem, a public insurance system for climate losses is emerging in the EU. The initiative envisages that the EU would establish a common public mechanism to complement private insurance markets and help stabilize insurance availability in times of increasing risks. The proposal also includes strengthening European disaster risk management through a fund financed by Member States, which would support the restoration of public infrastructure after natural disasters and mitigate the fiscal impact on individual countries. A system designed in this way should help bridge the growing gap between actual losses and what is covered by insurance, while ensuring that public property, infrastructure, and EU citizens remain protected in the future.

The way in which the state currently manages entrusted assets reflects its responsibility, efficiency, and ability to strategically manage public resources.

Given the diversity of public property, there is no single model that determines which assets should be insured as a priority. In developed countries such as the United Kingdom, the Netherlands, Finland, Denmark and Austria, it is standard practice not to insure public property commercially at all. Central government organisations do not normally use commercial insurance. The state has access to financial resources that enable it to absorb and manage various risks without the need for commercial insurance. This model allows the state to bear the costs of damage more cheaply and cover risks itself, from its budget (HM Treasury, 2025).

In Slovakia, an average of EUR 23 million per year was paid in insurance premiums in central government in 2016-2023. The current public procurement system is unable to generate genuine competition, which may contribute to less favourable insurance policies. Public procurement almost always uses only the lowest price criterion. (MF SR, 2025 Homola, 2025, CRZ, 2024).

Expert recommendations in this area emphasise the need for regular reassessment of insurance coverage, updating it according to the value and criticality of assets, as well as the introduction of combined financing mechanisms that increase the flexibility and resilience of the system. The World Bank Group (2021) also calls for a thorough risk analysis and the development of financial strategies tailored to the specific conditions of individual countries or regions. Such an approach enables states to effectively manage risks, protect public assets and ensure the continuity of public services even in times of crisis.

Insurance of public assets in European countries is a complex decision-making system influenced by legislative frameworks, economic rationality, budgetary policy and technological innovations (EC, 2020). Based on data analysis, countries can be divided into three main categories according to the degree of obligation and the way insurance is used.

1. Compulsory insurance - Bulgaria have introduced a legislative obligation to insure public property, particularly buildings, with coverage provided by the state budget (ECE, 2006, World Bank Group, 2021). This approach represents a centralised model where the state guarantees the protection of property through legal instruments.

2. Partial insurance - Countries such as Belgium, France, Germany and Slovakia apply selective insurance, focusing on strategic or valuable property (e.g. cultural monuments, IT infrastructure, vehicles). This model combines economic rationality with budgetary prudence, with the state often covering damages from reserve funds (CRZ, 2024; Homola, 2025).

3. Optional insurance / as needed - Most countries, such as the Czech Republic, Estonia, Finland, the Netherlands, Lithuania, Latvia, Luxembourg, Hungary, Poland, Slovenia and Sweden, do not apply blanket insurance to public property. Insurance is only used where it is economically justified or required by external entities (e.g. banks for mortgages). These countries prefer internal risk management mechanisms, budget reserves and, in some cases, modern tools such as AI (e.g. Estonia, Finland) to optimise asset management (EC, 2018a; EC, 2018b, Kratid, 2024).

European countries are characterised by a diversity of approaches to public asset insurance (EIOPA, 2024; ECB, 2023). While some countries prefer legislatively anchored models, others rely on flexibility, economic efficiency and technological innovation. The common denominator is the effort to optimise expenditure, increase the resilience of the public sector and manage risks effectively.

The processes of public risk management are increasingly shaped by the use of AI, which enables more accurate assessment of public asset risks, more reliable prediction of losses caused by natural disasters or technical failures, and more informed decision-making on preventive measures (Imran Sajid, 2025, Androniceanu, 2025). However, this also requires serious attention to the need for systematic risk management when deploying AI, as highlighted by the Federation of European Risk Management Associations (FERMA). FERMA emphasizes that public authorities must ensure adequate control mechanisms, transparency, and accountability when implementing high-risk AI systems (FERMA, 2024).

These considerations, along with other AI-related recommendations, are further reinforced by the European Insurance and Occupational Pensions Authority (EIOPA). EIOPA has published a supervisory statement addressed to national regulators, clarifying the key principles and requirements for the use and oversight of AI systems in the insurance sector (EIOPA, 2025).

2. Contributions and Potentials of Artifial Intelligence in Insurance Processes

In recent years, methods and techniques from AI have been developed and applied to problems and processes in the insurance domain (see Bhattacharya et al. 2025 for a survey). AI has gained significant momentum by the advances of machine learning, in particular deep learning (DL) approaches. DL excels in data-intensive domains, discovering patterns hidden in large amounts of data, elusive even for human experts. This applies to e.g. image data, tabular data, as well as mixtures thereof. Accordingly, DL methods have been applied for various tasks in the insurance domain, e.g. image processing in car damage classification (Hasan et al. 2025), detecting patterns in fraud detection and supporting risk scoring in underwriting (e.g. Gomes et al. 2021).

Many processes in insurances are still subject to manual processing. Hence, a more integrated apporach is called for. With the advent of generative AI, in particular large language models (LLM), a tighter integration and closer collaboration of humans and automated solutions becomes possible. LLMs are based on the Transformer architecture (Vaswani et al. 2017) and excel in understanding of textual documents, in the first place. Although the basic funtionality of transformers appears to be rather simple (next-token prediction), LLMs arguably acquire remarkable formal abilities relevant for language understanding (Mahowald et al., 2024).

LLM have the potential to enhance the operational efficiency of business processes in many areas, including the insurance domain. Concerning the finance and insurance domain, a number of papers discuss and explore the possibilities of using LLMs (including multimodal LLMs) for various standard tasks, such as Zhao et al. 2024 and Lin et al. 2024. Zhao et al. report that „GPT-4 effectively follows prompt instructions across various financial tasks“. Already in the current available versions, LLMs (including multimodal extensions) support critical decision-making processes in the insurance sector (cf. Lin et al. 2024).

Pretrained, bare LLMs can further be improved and adapted for specific tasks by ‚finetuning‘, feeding additional documents, or data in general, as corpus (Wei et al. 2022a). Fine-tuning can be done on a large cale (as in Wei et al.) or restricted to selected parameters as in Hu et al. 2022. Another well-established method is ‚retrieval-augmented generation‘ (RAG, Lewis et al 2020), where a corpus of data/documents is stored separately, and fast retrieval mechanisms allow matching input and relevant documents. The results of the match can then be used as input for an LLM. RAG allows providing further domain-specific context knowledge and enables LLMs to cope with questions otherwise beyond the built-in knowledge provided in the pretraining phase.

An important feature of LLMs, the investigation of which is currently still evolving in research, is that on the basis of available capacities and knowledge, further abilities move within practical reach. With ‚post-training enhancements‘ (Davidson et al. 2023), AI capabilities can be significantly improved without training, but with providing direct input to the LLM. Various techniques have been developed and are currently further tested, showing that evaluating the capabilities of LLMs is, at least partially, an empirical endeavor (cf. Dong et al. 2024). The abilities that occur in that process are sometimes called „emergent“, where the term is defined as „not within the reach of smaller models, but achievable for sufficiently large LLMs“ (for a discussion of the definition, see Wei et al. 2022b). An important aspect here is whether a specific ability is within the reach of a given LLM, which can usually not be predicted a priori, but needs further exploration. Furthermore, if the ability is not achieved with the help of a certain technique, it is still possible that another technique might be more successful.

The most popular and best known version of post-training enhancement is ‚prompting‘. Prompting techniques allows larger models solving tasks which are difficult or unsolvable for smaller models. Providing a few examples of tasks and their respective solutions („few-shot“) enable LLMs to learn how to perform tasks solely from context, without further training. Again, the ability in question might be out of reach for a smaller model given a specific prompt, but present for larger models.

Another now well-known technique is „chain of thought“ (CoT, Wei et al 2022b), where a task is solved by breaking it down into simpler steps which together solve the task. Larger LLMs can use CoT for solving difficult tasks successfully which they cannot solve without help/by default, when one or several examples of a task breakdown is provided. CoT requires no additional training, and leads to considerable improvements for e.g. mathematical, commonsense and symbolic reasoning.

Another enhancement consists in providing access to dedicated tools, such as web browser, calculator or other task-specific environments. Tool-use allows LLMs solving domain-specific tasks with higher precision and reliability. Here, the question of generality vs. narrowness of post-training enhancements comes to the fore. While tool-use might enhance the abilities of LLMs considerably for a specific task, other tasks which could be considered as related might still be out of reach.

Various versions of ‚scaffolding‘ aim at providing more generality. Tree-of-thought (ToT) is an advanced technique, where task descriptions are structured in a tree-like manner. Executing the task amounts to following the instructions in the task tree and evaluating the result of the execution. Depending on the result, different branches in the task tree can be selected for further execution.

Finally, Davidson et al. also considers agents as scaffolding environment. AI agents typically combine multiple post-training enhancements relating to prompting, scaffolding, and tool-use. Agents and ‚agentic AI‘ have in the meantime attracted a lot of attention in academia and the wider public. While the concept of autonomous agents was already present in the 1990s, the advent of LLMs made the concept come closer to reality. LLMs „serve as the reasoning core of a basic agentic system“ (Gulli 2025). Based on an understanding of a scenario, agents can break down complex tasks into single steps, execute the steps in an adaptive manner and react to unforeseen circumstances if necesary. The promise of agents is that through proactive and self-learning behavior, adaptive and scalable processes become possible, providing the ability to automate entire business workflows from start to finish. In this profound vision, the move from conventional rule-based automation to self-learning AI (Pingili 2025) could lead to integrated workflows which speed up processes, reduce cost, provide better accuracy and higher customer satisfaction.

The first model is predictive risk analytics for public infrastructure. Its objective is to estimate the probability of future damage to strategic public assets on the basis of historical claims data, current technical condition, and environmental exposure. Such a model can combine information on previous natural hazard events, technical inspections, and meteorological indicators and process them through machine-learning approaches such as gradient boosting. The practical value of this model lies in the possibility of prioritising preventive maintenance, identifying high-risk assets, and supporting selective insurance decisions instead of uniform coverage across all public property (Sheng & Fuchong, 2024).

The second model is fraud and anomaly detection in claims processing. This model focuses on identifying atypical claims by comparing current claim characteristics with previously observed patterns. Input data may include the type of property, declared loss amount, incident location, number of involved persons, descriptive claim documentation, and photographic evidence. By combining image analysis, text analysis, and comparison with reference repair-cost data, the model can flag suspicious or anomalous cases for further human review. In the context of public property insurance, such a model is particularly relevant for protecting public funds, strengthening procedural transparency, and accelerating the handling of legitimate claims (Eling et al., 2022; Saucé et al., 2023).

The third model is premium optimisation for public property portfolios. In this case, artificial intelligence can be used to differentiate insurance pricing and coverage recommendations according to the technical state of the asset, environmental exposure, functional importance of the object, and broader socio-economic conditions of the region. Penalised regression or similar optimisation approaches can be used to balance actuarial logic with fairness constraints, so that pricing reflects actual risk without creating disproportionate disadvantages for less affluent public entities. The main contribution of this model is the support of more efficient budget planning and more rational allocation of insurance expenditure in the public sector.

Taken together, these three models illustrate that the use of artificial intelligence in public property insurance can extend beyond document automation and claims support toward predictive, supervisory, and optimisation functions. They therefore represent analytically plausible directions for future practical implementation within an integrated public insurance framework (Nguyen et al., 2023; Eling et al., 2022; Thistlethwaite et al., 2020).

3. Research methodology

The main objective of the research was to conduct a comprehensive analysis of current approaches to public property insurance and use of AI in an international context. The research was designed as a systematic study based on the author's methodology, which included structured collection, classification, and critical evaluation of primary and secondary sources. The source base consisted of scientific publications, expert studies, legislative documents, and publicly available data sets.

The analysis focused on identifying and categorizing public property insurance models in European countries, especially the use of AI.

The research gap was identified in two areas:

1. Insufficient representation of the topic of public property insurance in professional literature – existing studies mainly focus on commercial insurance or individual insurance products, while the issue of the public sector is only dealt with in a fragmentary manner.

2. The absence of AI integration into insurance legislative frameworks – despite the growing importance of AI in risk prediction and asset management optimization, the legislative environment in most countries does not reflect this dimension at all. This deficit points to the need for interdisciplinary research that would combine technological, legal, and economic aspects and create a basis for proposing innovative solutions. This area is not the subject of this article and requires further scientific research, which is part of other scientific publications.

The identified gap is of fundamental importance because it suggests that current approaches to public property insurance do not take into account the potential of digital technologies, which may limit the effectiveness of risk management in conditions of dynamic social and environmental change.

Based on the knowledge gained, a conceptual model of integrated insurance process management will be proposed, combining three key dimensions:

1. predictive risk analysis based on the use of AI,
2. economic optimization of insurance strategies with the aim of minimizing costs,
3. digital management of public assets through automated systems (AI).

The nature of the proposed model is limited mainly by its conceptual and theoretical focus, which does not include empirical testing or implementation verification of the model in real public administration conditions.

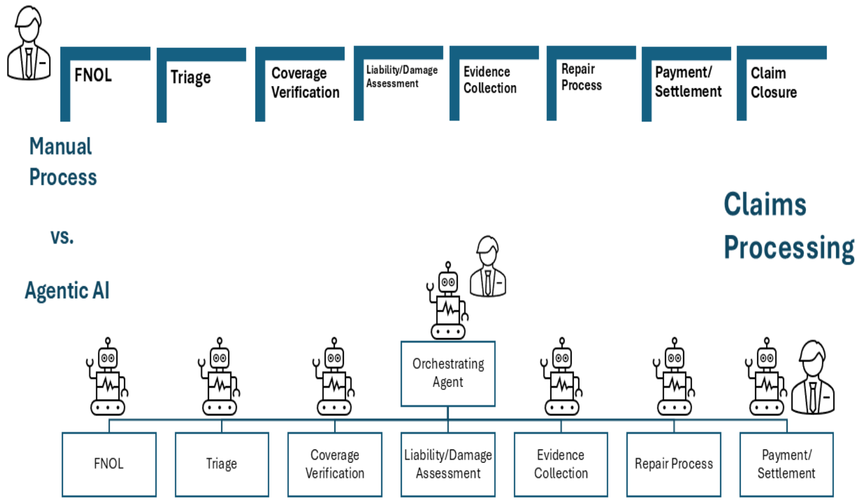
The synthetic data were used exclusively for illustrative purposes. Their role was not to replace empirical research, but rather to complement the conceptual model with a transparent data framework demonstrating the direction of variable effects, the logic of risk segmentation, and the feasibility of integrating statistical modelling with artificial intelligence. This approach reduces the purely theoretical character of the proposal and establishes a foundation for future validation using real-world data from public-sector institutions or insurance entities.

4. Research results and discussions

Workflows in insurances are heavily document-centered, so the abilities of LLMs and agentic AI for processing documents and understanding natural language texts can be harnessed to support the automation of insurance workflows. Examples are e.g. underwriting, product development, claims, and customer service. The following section focuses on the potential of AI in the field of insurance, using the example of insurance claims processing.

Claim processing (see Figure 1.) e.g. for cars or property insurance consists of a number of more or less standardised steps. A customer first issues a ‚first notice of loss‘ (FNOL) with information about the item (car, building etc.), the loss, location and other relevant data. In a second step (triage), the data is validated, checked for completenes, the damage categorized and the path for further processing selected. In coverage verification, the claim is compared with the policy and either confirmed or denied. Liability assessment checks the responsibilities, in the case of car accidents, of the parties involved, with potential fault splits occurring. Damage and injuries are assessed on the basis of the provided documents. Evidence collection is performed when the provided documents leave any issues outstanding. Then, the repair process is initiated or, in case of a total loss, the actual cash value is estimated. Finally, a settlement is reached and the case closed.

Figure 1. Claims processing – human vs AI



Source: own processing

Obviously, decisions in claims processing involve reading documents and digesting further information, in particular images e.g. of damages incurred. Based on these documents, the questions involved in the process have to be answered and decided. In a conventional, manual or rule-based enactment (figure 1, upper part), each decision has to be pre-specified in advance with instructions on how to use the information in the documents and adjucating the fulfillment of the regulations in question. In this case, any potentially occuring circumstance has to be anticipated in advance, including the format of inputs and outputs.

Several of these standard tasks have already been automated, from uploading documents and images, automated classifying images to fraud checking, where e.g. DL-based AI supports automating discrete tasks within the existing workflow. In the limit case, the vision is to perform the complete process in an automated way.

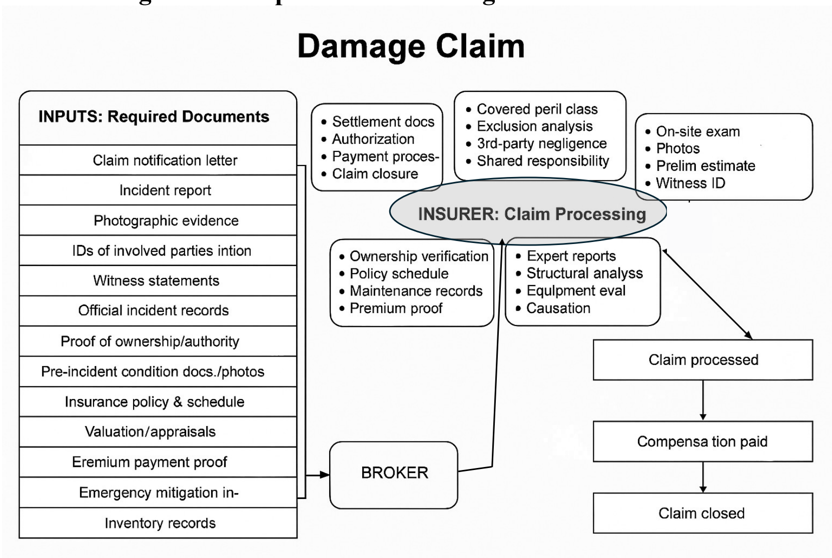
In the case of public property insurance, Slovak public authorities use brokers who are the first point of contact in the event of an insured event. Various authorities and institutions are responsible for this process in the public administration of the Slovak Republic, and they must comply with specific legislative and administrative procedures. Therefore, when concluding an insurance contract, public authorities must first carry out a public procurement procedure to ensure not only the lowest price, but above all the insurance conditions and reputation of insurers, so that the quality of the services provided and compliance with regulatory standards are guaranteed. In addition, factors such as transparency and efficiency must also be taken into account, resulting in rigorous control over the management of public funds and compliance with ethical standards in the selection and conclusion of insurance contracts. Once the public procurement process is complete, an insurance company is selected. In the case of public administration, new assets, appreciated assets, or new cars are not insured. Public authorities conclude framework agreements with insurance companies for a period of 5 years, with the value of the property to be insured specified in the insurance contract, and the value increased by a specified amount as agreed between the contracting parties. This increase ensures that in the event of innovation or the acquisition of new real estate, it will be covered by insurance and it will not be necessary to sign a new contract. In the Slovak Republic, it is standard practice in these contracts to increase the value of the insurance coverage by 10 to 15%. In the case of car insurance, these are automatically added to the fleet of insured vehicles. The final form of the insurance contract and its content are negotiated by a broker based on the requirements of the public administration. In practice, this often involves a situation where it is necessary to precisely identify the scope of coverage and include all essential contractual provisions, including exceptions and limits of coverage, which has a significant impact on the subsequent assessment of insurance claims (Windiantina et al., 2022). Setting up the insurance relationship this way lets both sides clearly understand the terms, while the pricing policy or coverage guarantees can also be influenced by global or national regulatory schemes (Fedoriuk, 2025). In property insurance, the location of the property, technical security measures against damage (e.g., alarms, fire protection systems), and the history of previous damage are analyzed. The result of the assessment is the classification of the client or the subject of insurance into a specific risk class. This classification then determines the amount of the premium, the coverage limits, and the form of exclusions from the contract. Insurance companies must ensure that this internal rating process is consistent with applicable legislation and does not contain unlawful discrimination (Gunarto et al., 2023). In a competitive market environment, pricing is influenced by the principle of arbitrage and risk-neutral valuation of the insurer's capital; cost estimates are also adjusted for expected returns on investment and shareholder preferences (Mirza & Wagner, 2018). The use of digital platforms with decentralized audit trails allows the insurance company to create a trustworthy history of interactions with the client without a single point of failure (Al Amin et al., 2024).

Current solutions combine computer vision, natural language processing, and automated workflows. This reduces the time needed to process an insurance claim from several days to hours. Efficiency is not only achieved by speeding up the process itself, but also by reducing manual errors and ensuring a higher degree of consistency in decision-making. Real-time telematics, the Internet of Things, and computer vision algorithms provide insurance companies with more accurate data for assessing damage. These systems can recognize different types of damage from multiple angles and then estimate repair costs with high accuracy. In practice, this means not only speeding up decisions on the amount of compensation, but also minimizing subjective human intervention in making estimates (Vamkeswaram, 2025). This trend is proving particularly effective in handling common mass events, where time savings have a significant positive economic impact. Integration with AI allows robotic process automation (RPA) to adapt to situations that previously required human judgment. AI-powered systems can handle unexpected data deviations and variable document structures with accuracy approaching that of humans when processing standard forms and handwritten notes. Insurance companies can thus reduce process processing costs by up to 40% compared to the normal state (Pingili, 2024) while maintaining a high level of quality of data entering decision-making mechanisms. AI is essential for fraud detection. Systems analyze historical data to find recurring patterns associated with previous fraudulent activities. The use of unlabeled datasets in combination with methods such as K-means offers flexibility, as it is not necessary to have complete and accurate annotations of all historical cases. Nevertheless, the risk of false positives must be taken into account, as some legitimate cases may exhibit atypical characteristics. This weakness requires feedback from human investigators who confirm or refute the classification of a case as fraud, thereby gradually optimizing the model. Clustering algorithms provide visualizations of groups in which individual insurance claims are placed according to similarity of characteristics (Agarwal, 2023). This allows the adjuster to see not only that the system has flagged a particular case as suspicious, but also the context of other events surrounding that case. This facilitates discussion between analysts and operational staff during the final assessment. From a broader solution architecture perspective, fraud detection systems are often integrated into the claims processing workflow so that disputed cases can be automatically redirected to specialized teams. The role of these teams is not to review all reports indiscriminately, but to prioritize those with the highest risk scores (Cherkaoui et al., 2024). This selective approach saves both manpower and investigation time. Similar principles have been successfully tested in various insurance segments (Ilham, 2024), where AI combines multiple analytical techniques and incorporates a wide range of input variables to increase the likelihood of a correct verdict in real time.

After closing an insurance claim (see Figure 2.), comprehensive document retention is a mandatory obligation of Slovak state authorities in order to demonstrate effective management of public funds. Public institutions must systematically retain all materials related to claims within the organization's record management systems for specified retention periods, which typically range from five to ten years, depending on institutional guidelines and applicable regulations.

AI speeds up the processing of insurance claims, automates the extraction of data from contracts, compares clauses with internal rules, detects discrepancies, reduces errors resulting from manual work, increases the consistency of decisions, and shortens the time needed to conclude an insurance relationship. In conjunction with autonomous agents that coordinate sub-tasks, an environment is created in which data flow operations, economic analyses, and decision-making processes are combined into a single integrated framework.

Figure 2. The process of handling an insurance claim



Source: own processing

By introducing and supporting AI in processes (Porlezza, 2023) related to public property insurance, the state will achieve greater efficiency, accuracy, shortening the cycle of creating an insurance contract and its approval, thereby saving resources and reducing bureaucracy. In the case of evaluation and risks in the process of insuring public property, the principle of linking AI analytical tools with structured and unstructured data from various sources is used. AI systems work simultaneously with historical damage data, technical characteristics of assets, location and environmental data, as well as documents, contracts, photographs, and text messages that are typical for public insurance processes. Since AI can identify complex relationships and patterns that would be invisible to a human analyst, it is possible to predict the probability of future events and support decisions about which assets should be commercially insured, which should be left to budget reserves, and where the optimal limits of co-participation or coverage lie.

A synthetic dataset was constructed as an illustrative analytical dataset to demonstrate the feasibility of the proposed model under conditions in which harmonised and fully accessible real-world microdata on public property insurance claims are unavailable. The dataset comprised 400 observations, each representing either a single public asset or a homogeneous group of assets included in the insurance decision-making process. Reproducibility was ensured by fixing the random seed at 42.

The structure of the synthetic data was designed to integrate variables of an economic, technical, operational, and informational nature (see Table 1.). The asset value (AV) variable was generated from a log-normal distribution, thereby producing the realistic right-skewed pattern typically observed in asset portfolios containing several high-value items. For this variable, the mean was EUR 6.949 million, the median EUR 5.618 million, the minimum EUR 0.557 million, and the maximum EUR 79.950 million, with a skewness coefficient of 5.207, confirming a pronounced right tail in the distribution.

The asset age (AGE) variable was generated as a discrete variable ranging from 1 to 60 years. The mean age was 29.527 years, the median 30 years, the first quartile 14 years, and the third quartile 45 years. The distribution of this variable was nearly symmetrical, with a skewness coefficient of only 0.047.

The claims history (CH) variable for the previous five years was generated from a Poisson distribution with a parameter of 1.8 in order to capture the frequency of past claims. In the synthetic dataset, its mean was 1.810, the median 2, and the standard deviation 1.339. The frequency distribution indicated that 64 units reported no claims, 121 units reported one claim, 107 units reported two claims, 65 units reported three claims, 24 units reported four claims, 16 units reported five claims, and 3 units reported six claims.

The variables climatic exposure (CE), technical protection (TP), asset criticality (AC), and data quality (DQ) were modelled as ordinal scales ranging from 1 to 5. For climatic exposure, the mean was 3.045, and the distribution across categories was as follows: 74 observations in category 1, 80 in category 2, 76 in category 3, 94 in category 4, and 76 in category 5. For technical protection, the mean was 3.085, with frequencies of 84, 56, 90, 82, and 88 units in categories 1 to 5, respectively. Asset criticality had a mean of 2.980, with a distribution of 85, 76, 78, 84, and 77 observations across the five categories. Data quality had a mean of 2.935, with 90, 72, 87, 76, and 75 observations in categories 1 to 5, respectively.

The binary outcome variable, claim occurrence, was generated on the basis of a latent linear predictor, which was subsequently transformed using the logistic function (1) to obtain the event probability. The linear predictor took the form:

$$z=-3+0.20*AV+0.035*AGE+0.48*CH+0.42*CE-0.55*TP+0.33*AC-0.28*DQ \quad (1)$$

and the probability of a claim event was defined as $p = 1/(1 + \exp(-z))$. The binary outcome itself was then simulated from a Bernoulli distribution with parameter p. This procedure ensured that the synthetic data were not generated arbitrarily, but instead reflected an explicitly defined risk structure in which a more extensive claims history, greater climatic exposure, higher asset criticality, and higher asset value increased risk, whereas stronger technical protection and higher data quality reduced it.

The generated outcome variable comprised 196 positive cases and 204 negative cases, meaning that the proportion of claims in the dataset was 49.0%. The mean latent probability of a claim event was 0.497, the median 0.490, the minimum 0.015, and the maximum approximately 1.000 after rounding. Configured in this manner, the dataset provided a balanced testing environment for the illustrative validation of the classification model. With regard to the relationships between the explanatory variables and the outcome, the strongest linear associations with claim occurrence in the synthetic dataset were observed for asset value (correlation 0.242), asset criticality (0.225), asset age (0.210), claims history (0.207), and climatic exposure (0.159). Negative associations were observed for technical protection (-0.239) and data quality (-0.131). These results are consistent with the logic of the data-generation mechanism and confirm that the synthetic dataset constitutes an internally coherent and analytically usable basis for pilot modelling.

Table 1. Summary statistics of the synthetic dataset

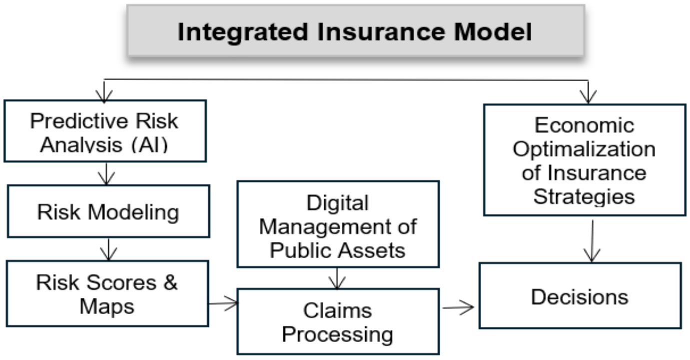
Variable	Mean	Med	Std. dev.	Min	Q1	Q3	Max
Asset_value	6,959	5,618	6,175	0.557	3,406	8,381	79,950
Age_of_assets	29,527	30,000	17,721	1,000	14,000	45,000	60,000
Claims_history	1,810	2,000	1,339	0.000	1,000	3,000	6,000
Climate_expos.	3,045	3,000	1,392	1,000	2,000	4,000	5,000
Tech. protection	3,085	3,000	1,436	1.000	2,000	4,000	5,000
Asset_criticality	2,980	3,000	1.423	1.000	2,000	4,000	5,000
Data_quality	2,935	3,000	1,422	1,000	2,000	4,000	5,000
Insurance_claim	0.490	0.000	0.501	0.000	0.000	1.000	1.000

The proposed model (see Figure 3.) also emphasizes that the individual components are not isolated, but form a continuous feedback loop. The model supports data-driven decision-making and increases the ability of public institutions to respond to a changing risk environment.

In connection with this, it is necessary to ensure the use of advanced statistical methods in the field of insurance analytics as an essential basis for the application of artificial intelligence. Predictive models in insurance achieve the highest accuracy thanks to the support of statistical data processing, including probability modeling, time series, variability and extreme value analysis, and dimensionality reduction. (Bhattacharya et al. (2025).

The predominantly theoretical nature of the model allows for the creation of a framework that is flexible enough to be adaptable to different public administration conditions, which vary significantly in terms of digitization, data quality, and organizational maturity. The model is deliberately formulated as conceptual so as not to preempt future European or national standards for explainability, auditability, and governance of artificial intelligence systems, but to create a solid foundation that can later be harmonized with regulatory requirements without major interventions in the architecture. The variability of the institutional environment is therefore not an obstacle to implementation, but a test of the scalability of the solution, which naturally follows from the public law context for which the model is intended.

Figure 3. Integrated Insurance Model



Source: own processing

5. Conclusions

This article points out that the issue of public property insurance in a dynamic risk environment is of strategic importance not only in terms of protecting public resources but also in terms of the long-term resilience of the public sector. An analysis of European approaches confirms a gradual shift away from blanket commercial insurance towards selective, economically justified, and data-driven solutions. The proposed integrated insurance process management model, which combines AI-based predictive risk analysis, economic optimization of insurance strategies, and digital management of public assets through automated systems and autonomous agents, is therefore not only a theoretical but also a practical tool. The model combines predictive risk analysis based on artificial intelligence, economic optimization of insurance strategies, and digital management of public assets through automated systems and autonomous agents.

The modular structure and high parameterizability of the components ensure transferability and adaptability to the individual conditions of each country or institution. The proposed model goes beyond existing approaches by transforming the role of AI from a complementary tool to a central decision-making mechanism, particularly in risk prediction, documentation automation, and fraud detection. It also expands the importance of economic optimization and enables continuous updating of asset risk profiles based on live data, creating a real-time learning system. The modular architecture and high flexibility of the model's implementation allow individual components to be adapted to the specific needs of different countries or institutions, making it a universally applicable concept. Although the proposed model is currently a theoretical concept, its basic principles suggest that the future paradigm of public asset insurance will inevitably be based on the synergy of technological sophistication, economic rationality, and modern approaches to public asset management. The proposed model represents a robust and promising framework that significantly enriches the current state of knowledge, opens up space for further academic discourse, and creates a solid foundation for subsequent regulatory development and practical implementation in the public administration environment.

Conflict of interest

We declare that the author's team has conducted research without any business or financial relations that could be interpreted as a potential conflict of interest.

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