



HELLENIC OPEN UNIVERSITY

Master in Business Administration (MBA)

Postgraduate Dissertation

The Adoption and Implementation of
Artificial Intelligence in the Insurance
Industry

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Patras, Greece, May 2026

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I would like to express my sincere gratitude to my supervisor, Mrs. Niki Glaveli, for her constant guidance, support, and valuable advice throughout the completion of this dissertation.

I would also like to sincerely thank Mr. Ioannis Katsanakis, co-supervisor of this dissertation, for his support and contribution throughout this research. In addition, I would like to thank all the participants from the insurance companies who took part in this research and contributed their time and insights. Finally, I would like to thank my friends, and above all my family, for their unwavering support and encouragement throughout all these years.

Abstract

This dissertation investigates the factors influencing employees' intention to adopt Artificial Intelligence (AI) in the insurance industry, focusing on technological, organizational, environmental, and human factors. Particular emphasis is placed on the mediating role of human factors in the relationship between these factors and AI adoption intention. A quantitative research approach was employed using a structured five-point Likert questionnaire. The study sample consisted of 120 employees working in insurance companies in the Attica region, Greece. Data were analyzed using descriptive and inferential statistics, reliability analysis, Pearson correlations, multiple linear regression, and mediation and moderation analyses. The findings indicate that employees hold generally positive attitudes toward AI and demonstrate a high intention to adopt AI applications. Although all major factors were positively associated with AI adoption intention, human factors emerged as the strongest and only statistically significant direct predictor. Furthermore, technological, organizational, and environmental factors influenced adoption intention primarily through their indirect effect on human factors, while no significant moderation effects were identified. Previous AI experience, higher digital skills, and company size were also associated with stronger adoption intention. Overall, the study concludes that the successful implementation of AI in the insurance industry depends not only on technological and organizational readiness but, more importantly, on employees' attitudes, trust, digital competence, and willingness to embrace technological change.

Keywords

Artificial intelligence, insurance industry, AI adoption, human factors, organizational factors, digital skills, insurance companies

Περίληψη

Η παρούσα διπλωματική εργασία διερευνά τους παράγοντες που επηρεάζουν την πρόθεση υιοθέτησης της Τεχνητής Νοημοσύνης (Artificial Intelligence-AI) στον ασφαλιστικό κλάδο, εστιάζοντας στον ρόλο των τεχνολογικών, οργανωσιακών, περιβαλλοντικών και ανθρώπινων παραγόντων. Ιδιαίτερη έμφαση δίνεται στον διαμεσολαβητικό ρόλο των ανθρώπινων παραγόντων στη σχέση των υπόλοιπων παραγόντων με την πρόθεση υιοθέτησης της AI. Η έρευνα ακολούθησε ποσοτική μεθοδολογική προσέγγιση με τη χρήση δομημένου ερωτηματολογίου πέντε βαθμίδων Likert. Το δείγμα αποτέλεσαν 120 εργαζόμενοι ασφαλιστικών εταιρειών στην περιοχή της Αττικής. Για την ανάλυση των δεδομένων εφαρμόστηκαν περιγραφικά και επαγωγικά στατιστικά, έλεγχοι αξιοπιστίας, συσχετίσεις Pearson, πολλαπλή γραμμική παλινδρόμηση, καθώς και αναλύσεις διαμεσολάβησης και τροποποίησης. Τα αποτελέσματα έδειξαν ότι οι εργαζόμενοι διατηρούν γενικά θετική στάση απέναντι στην Τεχνητή Νοημοσύνη και εμφανίζουν υψηλή πρόθεση υιοθέτησής της. Όλοι οι βασικοί παράγοντες συσχετίζονται θετικά με την πρόθεση υιοθέτησης, ωστόσο οι ανθρώπινοι παράγοντες αναδείχθηκαν ως ο ισχυρότερος και μοναδικός στατιστικά σημαντικός άμεσος προγνωστικός παράγοντας. Επιπλέον, διαπιστώθηκε ότι οι τεχνολογικοί, οργανωσιακοί και περιβαλλοντικοί παράγοντες επηρεάζουν την πρόθεση υιοθέτησης κυρίως έμμεσα, μέσω των ανθρώπινων παραγόντων, ενώ δεν εντοπίστηκε στατιστικά σημαντική τροποποιητική επίδραση των παραγόντων αυτών στη σχέση ανθρώπινων παραγόντων και πρόθεσης υιοθέτησης. Παράλληλα, η προηγούμενη εμπειρία χρήσης AI, το επίπεδο ψηφιακών δεξιοτήτων και το μέγεθος της επιχείρησης συνδέθηκαν με υψηλότερη πρόθεση υιοθέτησης. Συνολικά, τα ευρήματα υποδεικνύουν ότι η επιτυχής ενσωμάτωση της Τεχνητής Νοημοσύνης στον ασφαλιστικό κλάδο δεν αποτελεί μόνο τεχνολογική ή οργανωσιακή πρόκληση, αλλά εξαρτάται κυρίως από την ετοιμότητα, την εμπιστοσύνη, τις δεξιότητες και τη θετική στάση των εργαζομένων απέναντι στις νέες τεχνολογίες.

Λέξεις – Κλειδιά

Τεχνητή νοημοσύνη, ασφαλιστικός κλάδος, υιοθέτηση AI, ανθρώπινοι παράγοντες, οργανωσιακοί παράγοντες, ψηφιακές δεξιότητες, ασφαλιστικές εταιρείες.

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List of Abbreviations & Acronyms

Acronyms	Definition
AI	Artificial Intelligence
ANOVA	Analysis of Variance
A.P.	Arithmetic Mean / Average price
BootLLCI	Bootstrap Lower Limit Confidence Interval
BootULCI	Bootstrap Upper Limit Confidence Interval
CI	Confidence Interval
HSD	Honestly Significant Difference
IBM	International Business Machines
ICT	Information and Communication Technology
IEK	Institute of Vocational Training
LLCI	Lower Limit Confidence Interval
MSE	Mean Squared Error
P-P Plot	Probability–Probability Plot
S.D.	Standard Deviation
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TOE	Technology–Organization–Environment
ULCI	Upper Limit Confidence Interval
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

1. Introduction

Artificial Intelligence (AI) is currently one of the most dynamic axes of digital transformation. Its impact is already visible in many sectors of the economy, but in the insurance sector it acquires particular importance, as it is directly linked to risk assessment, pricing, claims management, customer service and new product design. Its importance, therefore, is not limited to the automation of individual functions. It extends to the overall reshaping of the insurance value chain and the way insurance businesses organize their processes and produce services (Eling et al., 2022).

This development creates significant opportunities for the insurance industry. AI can help make better use of available data, improve forecast accuracy, reduce process turnaround time, and shape more personalized customer services. At the same time, however, its adoption is accompanied by substantial challenges. Data protection, transparency of algorithmic decisions, compatibility with already existing information systems, regulatory compliance, and user trust are factors that decisively influence whether and to what extent a business can effectively integrate such technologies (Eling et al., 2022; Gupta et al., 2022).

For this reason, the adoption of AI cannot be seen as just a technical issue. The international literature shows that this is a multifactorial phenomenon, in which technological, organizational, environmental and human dimensions interact. The Technology–Organization–Environment framework highlights the importance of technological characteristics, organizational readiness, and pressures from the external environment, while technology acceptance approaches highlight the role of perceived utility, usability, self-efficacy, perceived risk, and user attitudes towards new technology (Gupta et al., 2022; Nguyen et al., 2024). In other words, the success of AI depends not only on what the technology itself can do, but also on how it is understood, accepted, and exploited by the people who are called upon to use it.

This observation is particularly critical in the insurance industry. This is an area where decision-making is based on data, risk assessments, regulatory rules and relationships of trust with the customer. In such an environment, the introduction of AI doesn't just change the tools available; It affects roles, professional practices, organizational balances and the way in which human judgment is evaluated at work. That is why the study of the adoption of AI by employees becomes particularly important, as

they themselves are the essential link between technological capability and its actual application in the organization (Gupta et al., 2022; Nguyen et al., 2024).

In this context, this thesis examines the factors that influence the intention to adopt AI in the insurance industry. In particular, it focuses on technological, organizational, environmental, and human factors, as well as their direct and indirect role in shaping the intention to use AI applications. At the same time, it explores the role of human factors as a mediation mechanism and approaches the issue of the adoption of AI in relation to organizational efficiency and service delivery. The survey was conducted on 120 employees of insurance companies from the area of Athens, Attica, in order to capture the perceptions, attitudes and level of readiness of a real professional population towards the use of AI.

The importance of the present study is twofold. On the one hand, it aspires to contribute to the understanding of a phenomenon that is evolving rapidly and increasingly affecting the operation of insurance companies. On the other hand, it approaches AI not as a neutral technological innovation, but as a process of organizational change that requires strategy, support, skills, adaptation, and trust. In this sense, the paper seeks to contribute both to the theoretical debate on the adoption of AI and to the formulation of more meaningful directions for practice in the insurance space (Eling et al., 2022; Nguyen et al., 2024).

The thesis is structured in seven chapters. The *first chapter* is the present introduction. The *second chapter* presents the theoretical background of the study, with emphasis on the definition of AI, its historical development in the insurance industry, its basic applications and the main theoretical models of technology adoption. It describes the methodology of the research, i.e. the research design, the sample, the research tool, the data collection process, the methods of analysis and the issues of reliability and validity. The *fourth chapter* presents and analyzes the empirical results, proceeds to their discussion in relation to the research questions and the theoretical framework of the thesis. Finally, the *fifth chapter* summarizes the main conclusions of the study, highlights the contribution of research, records its limitations and formulates proposals for both the insurance industry and future research investigation.

Based on the above, the main purpose of this dissertation is to investigate the factors influencing the adoption of AI in the insurance industry, with particular emphasis

on the role of technological, organizational, environmental, and human factors in shaping employees' intention to adopt AI applications.

More specifically, the study aims to:

- examine employees' perceptions of the technological, organizational, environmental, and human factors related to AI adoption;
- investigate the relationships between these factors and AI adoption intention;
- assess the direct and indirect effects of technological, organizational, environmental, and human factors on AI adoption intention;
- examine the mediating role of human factors in the relationship between technological, organizational, and environmental factors and AI adoption intention;
- investigate whether technological, organizational, and environmental factors moderate the relationship between human factors and AI adoption intention; and
- explore whether demographic and occupational characteristics are associated with employees' intention to adopt AI.

To address these objectives, the following research questions were formulated:

RQ1. What are the perceptions of insurance company employees regarding the technological, organizational, environmental, and human factors associated with AI adoption?

RQ2. What are the relationships between technological, organizational, environmental, and human factors and AI adoption intention?

RQ3. To what extent do technological factors influence AI adoption directly and indirectly through human factors?

RQ4. How do organizational factors influence AI adoption, and to what extent is their influence mediated by human factors?

RQ5. How do environmental factors influence AI adoption, and what is the indirect role of human factors?

RQ6. What is the direct role of human factors in shaping AI adoption intention?

RQ7. Do human factors mediate the relationship between technological, organizational, and environmental factors and AI adoption?

RQ8. Do technological, organizational, or environmental factors moderate the relationship between human factors and AI adoption intention?

RQ9. To what extent are employees' demographic and occupational characteristics associated with AI adoption intention?

2. Theoretical Background

2.1 Introduction

This section presents the theoretical framework of the study, focusing on the adoption and application of artificial intelligence (AI) in the insurance industry. Its main objective is to provide a clear framework at both an interpretive and conceptual level. Through this framework, the study seeks to facilitate the understanding of the empirical findings that follow, particularly those related to the intention of insurance companies to adopt AI-based solutions. To achieve this, key definitions, the historical development of applications, and theoretical models of technology adoption are presented in a structured way, in order to outline the main elements and factors that influence organizational decision-making in the sector under examination.

More specifically, section 2.2 begins with the definition of AI, addressing both the general scientific perspective and more specialized forms that are directly linked to insurance services. These include machine learning systems, automated decision-making systems, and chatboxes used in customer service. The purpose of this approach is to clarify how AI is understood within the context of the study, ensuring that the analyses that follow are grounded in a shared conceptual basis.

Section 2.3 then presents a historical overview of how AI has evolved in the industry. It covers early forms of automation and simple statistical models, leading up to more advanced and sophisticated solutions that support risk prediction, product personalization, and fraud detection. This overview highlights the stages of technological maturity, as well as the factors that accelerated adoption, such as data digitization and increased competition.

Next, subsection 2.4 focuses on the main applications of AI in the modern insurance sector. It discusses automated pricing, claims management, real-time risk analysis, and improvements in customer experience. The aim is not only to describe these applications, but also to show how AI is reshaping business processes and business models.

Section 2.5 follows with a presentation of the main theoretical models of technology adoption. Particular attention is given to the Technology Acceptance Model, the Technological–Organizational–Environmental framework, and the Unified Theory of

Acceptance and Use of Technology. These models provide a structured way to understand the factors that influence both organizational attitudes and behavior.

In subsection 2.6, these models are applied to the insurance sector, grouping the relevant factors into technological, organizational, environmental, and human-centered categories. Each category is examined through specific dimensions, such as the scope and capabilities of AI, organizational culture and strategy, the regulatory environment, and perceptions and trust.

Finally, the chapter concludes with subsection 2.7, which summarizes the theoretical discussion. It also presents the research hypotheses regarding the relationship between the four groups of factors and the intention to adopt AI.

2.2 Definition of Artificial Intelligence (AI)

AI refers to a set of concepts and technologies that describe systems capable of performing tasks that traditionally require human intelligence. These tasks include learning, reasoning, decision-making, and adapting to changing environments (Bhattacharya, 2025). In the context of this study, AI is not seen simply as a single technique. Instead, it is understood as an ecosystem made up of algorithms, data, and computing power that interact with each other. The purpose of these interactions is to automate, support, or improve human processes in the insurance industry (Acosta-Prado, 2024). In this sense, AI can be described as a field within computer science that focuses on designing and implementing systems able to learn from data, recognize patterns, and predict future outcomes, with the aim of improving decisions and results (Hassani, 2020). This broad concept includes several subfields, such as machine learning, deep learning, natural language processing, and recommender systems, which together reflect different aspects of intelligent system behavior (Owens, 2022).

At the same time, a distinction is often made between narrow AI and general AI. Narrow AI refers to systems designed to perform specific tasks, while general AI describes hypothetical systems with a wide range of cognitive abilities similar to those of humans. In practice, the insurance industry mainly uses narrow AI (Cevolini, 2020). The way AI is defined is also shaped by how it is applied in each sector. In finance and insurance, the focus is on predicting risk, personalizing pricing, and managing large volumes of customer data (Aleksandrova, 2023). From this point of view, AI can be seen both as a

technological infrastructure and as a strategic resource, since it supports the shift from traditional statistical tools to systems that offer automation, flexibility, and real-time decision-making (Pugnetti, 2021).

In terms of functional definitions, AI is usually described as a set of technologies that can improve or replace human cognitive functions within specific organizational processes. Examples include risk assessment, fraud detection, and claims management (Atlasi, 2025). A key element in these definitions is data-driven learning, which distinguishes AI from traditional programming systems that rely on fixed rules and remain static (Kaushik, 2022). AI systems, by contrast, update their models using new data and feedback. As a result, they continuously improve their accuracy and the usefulness of their predictions, especially in dynamic environments such as insurance (Kapse, 2025).

In the insurance sector in particular, AI is also defined by its ability to combine data from multiple sources. These sources include historical claims data, demographic information, telematics sensors, and customers' digital footprints. This integration helps build detailed profiles of risks and behaviors (Hanafy, 2021). In this way, AI acts as a mechanism of social categorization, which can influence issues related to fairness, transparency, and discrimination in insurance practices (Gramegna, 2020).

Beyond these aspects, AI is increasingly viewed as a socio-technical system. Its performance and impact depend not only on how algorithms are designed, but also on how they are integrated into organizational structures, workflows, and regulatory environments (Islam, 2023). Research on technology adoption in organizations also provides an operational definition of AI. According to this view, AI includes any tool that uses advanced learning algorithms to automate and support complex decisions under conditions of uncertainty (Song, 2025). This definition allows AI to be linked with established models such as the Technology Acceptance Model, where perceived usefulness and ease of use are directly connected to intelligent systems (Ibrahim, 2025).

Similarly, approaches based on the Technology–Organization–Environment framework describe AI as a combination of technological features, organizational capabilities, and external pressures. This means that its definition is closely tied to the context in which it is implemented (Sánchez, 2025). For instance, in knowledge-intensive sectors like insurance,

AI is often defined by its role in redesigning processes and reshaping complex cognitive tasks (Yang, 2024).

As a result, the concept of organizational readiness contributes to broader definitions of AI that go beyond technical aspects. These definitions also include factors such as employee skills, organizational culture, and strategy. Such elements play a key role in determining whether AI systems can actually create value (Hradecký, 2022). From this perspective, AI is no longer just a set of tools. It is seen as a dynamic capability that allows organizations to combine data, technologies, and human resources in order to support continuous learning and innovation in decision-making (Hržica, 2025). The definition has expanded further with the rise of generative AI, as systems are now able not only to predict but also to generate text, images, and code, opening new possibilities for use in the insurance sector (AI-kfairy, 2025).

Finally, the ethical and regulatory dimension is also important in defining AI. This perspective focuses on the ability of systems to produce desired outcomes without reinforcing bias, lacking transparency, or misusing data. As a result, principles of responsible and trustworthy innovation are included in its definition (AI-kfairy, 2024). It is also important to note that, from the user's perspective, AI is shaped by perceptions of intelligence, autonomy, and social presence, which directly influence attitudes and intentions toward its use (Kim, 2024). At the operational level, AI is treated as a set of digital innovations that connect data management, analytical models, and emerging business models, contributing to changes in how value is created and captured, especially in small and medium-sized enterprises (Badghish, 2024).

2.3 Historical overview and development of AI Adoption in the Insurance Industry

The evolution of AI in the insurance industry is closely linked to the stages of digitalization and the shift from manual processes to automated information systems (Hassani, 2020). In the early years, the sector relied on quantitative methods, with classical statistical models dominating pricing and loss prediction. These models were based on limited datasets and strict actuarial assumptions (Boodhun, 2018). Over time, however, computing power increased and the use of large datasets expanded. This created the

conditions for the introduction of more advanced, algorithm-based approaches aimed at improving risk identification and management (Rustam, 2018).

An important step toward AI adoption was the use of machine learning techniques in various applications. These included predicting insurance company bankruptcies and classifying portfolios according to risk levels (Boodhun, 2018). At the same time, the strong foundation in actuarial science supported the gradual adoption of more flexible models. Actuaries began to combine traditional pricing methods with classification and regression algorithms, marking a shift toward more adaptive analytical approaches (Hassani, 2020).

As insurance claims became more frequent and complex, there was growing pressure to automate analytical processes. This development accelerated the adoption of techniques that are now recognized as AI (Amerirad, 2023). With the arrival of the 21st century, digital sales channels and online underwriting platforms expanded significantly. These developments generated large volumes of data, which became the basis for more advanced models focused on prediction and segmentation (van den Broek-Altenburg, 2019). In this context, early commercial systems close to AI focused on improving pricing and identifying behavioral patterns linked to higher risk, mainly through supervised machine learning methods (Kaushik, 2022). In addition, the development of telematics in vehicle insurance enabled the collection of real-time data on driving behavior. This shift supported the move from standard tariffs to dynamic, personalized pricing based on learning algorithms (Hanafy, 2021). As a result, AI began to play a broader role, not only in analysis but also in shaping the relationship with customers, as pricing and offers became continuously adjusted based on user behavior (Gramegna, 2020).

The widespread use of mobile devices and the growth of digital footprints through social media further expanded the data available to insurers. This allowed companies to better understand consumer attitudes and expectations regarding insurance products. As a result, the range of data sources increased significantly, strengthening the development of algorithmic models (van den Broek-Altenburg, 2019). During this period, systematic discussions on the use of algorithmic practices also emerged, reflecting changes in how organizations approached risk allocation (Cevolini, 2020).

Beyond commercial use, academic research on loss prediction and fraud detection using machine learning has grown considerably. This reflects a broader shift toward non-parametric and hybrid models (Yang, 2018). In health insurance, the development of advanced models for predicting costs in high-risk groups marked a key step in integrating AI into pricing and product design. These models also demonstrated how algorithmic approaches can improve resource allocation (Yang, 2018). At the same time, research began to focus on predicting costs at the individual policyholder level using regression and deep learning techniques, further supporting the development of personalized insurance products (ul Hassan, 2021). In parallel, studies on explainable algorithms for premium calculation highlighted the importance of transparency in pricing decisions (Kapse, 2025).

Gradually, especially in health insurance, systematic reviews began to document how AI applications evolved over time. These reviews show a progression from simple data management tools to more complex decision-support systems (Ramezani-a, 2025). They also highlight the exploration of hybrid approaches that combine neural networks with traditional methods, indicating a growing level of maturity in the field (Hanafy, 2021).

In general insurance, the historical development is reflected in comparative studies of algorithms used for loss prediction and risk assessment, particularly in areas such as property insurance. These studies evaluate different machine learning models in terms of accuracy and practical usefulness (Ejiyi, 2022). Research on predicting insurance company insolvency using support vector machines also illustrates the shift toward tools capable of analyzing financial risk and economic behavior patterns (Rustam, 2018).

At the same time, explainable predictive models were developed to better understand consumer decisions, such as the choice to purchase insurance. This shows that AI development is not limited to risk management but also extends to analyzing consumer behavior and motivations (Gramegna, 2020). Another important development is the emergence of peer-to-peer insurance models, where AI supports new organizational structures and collective approaches to risk sharing (Horvey, 2025). In parallel, the broader development of technological infrastructures in the financial sector led to the rise of the term “Insurtech.” This term describes a growing ecosystem of start-ups that use AI, big data, and automation to create new insurance services and business models (Aleksandrova, 2023). In this context, AI is used to deliver value-added digital services,

such as personalized risk prevention advice and continuous behavior monitoring through connected devices (Pugnetti, 2021).

At the same time, traditional insurance companies began adopting explainable AI tools, aiming to balance the power of complex models with the need for transparency and interpretability, especially for regulatory and ethical reasons (Owens, 2022). This shift reflects increasing awareness of the risks associated with opaque algorithms, particularly in sectors where decisions directly affect access to essential services and financial well-being (Al-kfairy, 2024). There is also evidence that AI can introduce new risks related to manipulation, which has led research to focus on adversarial practices and algorithmic vulnerabilities (Amerirad, 2023).

As AI techniques became more advanced and widely used, the need to systematically map their applications became more evident. This led to studies examining the evolution of scientific research and identifying key areas of focus (Atlasi, 2025). These analyses show that early research was mainly technical, while more recent work increasingly addresses social, regulatory, and organizational issues, reflecting the gradual maturity of the field (Bhattacharya, 2025). In this context, organizational readiness has become a critical factor, as successful AI adoption depends on the ability of insurance companies to adapt their structures, processes, and skills to new technological demands (Hradecký, 2022).

Overall, current research indicates that the insurance sector is in a transitional phase of broad development, with AI playing a central role in shaping sustainability strategies and competitive advantage (Acosta-Prado, 2024). This transformation also brings attention to the skills required from the workforce, as new roles emerge that combine traditional responsibilities with the supervision of algorithmic systems (Acosta-Prado, 2024). Finally, general attitudes toward AI adoption across industries suggest that the insurance sector is part of a wider trend of digital transformation, where the effective use of algorithms is essential for adapting to the modern environment (Badghish, 2024).

2.4 Applications of AI in the insurance industry

In recent years, AI has become integrated into almost every key part of the insurance value chain. This has changed how companies design products, assess risk, set policy prices, and interact with customers (Bhattacharya, 2025). In risk assessment and pricing, machine

learning models make it possible to process large volumes of data. These data help identify complex links between policyholder characteristics, claims history, and the likelihood of future claims, improving the accuracy and detail of premiums (Boodhun, 2018). In life and health insurance, such models are used to estimate coverage costs at the individual level by combining medical, demographic, and behavioral data, leading to a closer alignment between price and risk (Kaushik, 2022). In addition, regression and deep learning approaches support the development of systems where premiums can be adjusted dynamically, depending on changes in health status or service use, which allows for more targeted products (Hanafy, 2021). At the same time, explainable models are applied to show how specific factors influence the final premium. This supports compliance and improves communication with both customers and regulatory authorities (Kapse, 2025).

In health insurance in particular, AI is also used to predict which patients are likely to generate high costs. This allows insurers to identify high-risk cases early and design appropriate interventions and contracts (Yang, 2018). At the same time, computational intelligence models estimate medical costs for each insured person by combining multiple variables and algorithms to improve predictive accuracy (ul Hassan, 2021). Data from social media and digital activity are also used to better understand customer attitudes and preferences. This helps companies develop offers that are more adaptable and appealing, strengthening the effectiveness of their commercial strategies (van den Broek-Altenburg, 2019).

AI also plays an important role in improving claims management. It helps detect patterns that may indicate misuse or, on the contrary, appropriate use of services, protecting both policyholders and the financial stability of insurers (Bhardwaj, 2020). Learning systems analyze historical transaction data along with external sources to identify unusual behaviors and relationships (Amerirad, 2023). Based on this analysis, claims can be classified according to their risk of fraud, allowing investigators to focus on suspicious cases while speeding up the processing of legitimate ones (Aleksandrova, 2023). In this context, explainable AI helps clarify why certain claims are flagged as suspicious, reducing bias and increasing trust in the process (Owens, 2022).

Beyond operational processes, AI is also shaping new business models in the insurance industry. These models rely on data analysis to automate risk assessment and support more flexible forms of collective coverage (Horvey, 2025). Algorithms are used to match

individuals with similar risk profiles, calculate contributions, and distribute losses in a way that is transparent and acceptable to participants (Cevolini, 2020). A key driver of these developments is the insurtech ecosystem, which promotes rapid risk assessment, process automation, and personalized services (Bhattacharya, 2025). Through these platforms, insurers combine data from multiple external sources and digital transactions to build dynamic customer profiles, allowing continuous adjustments in coverage and pricing (Pugnetti, 2021). This shift toward more personalized, behavior-based products reflects how AI supports new forms of value creation and differentiation (Aleksandrova, 2023).

Customer service has also been significantly affected. AI-based chatbots are used to provide immediate responses, guide customers through contract processes, and offer updates on claims (Mukherjee, 2021). These systems can understand natural language, retrieve relevant information from internal databases, and tailor communication to each user. As a result, waiting times are reduced and customers feel better supported (Acosta-Enríquez, 2024). Their role goes beyond simple information delivery, as they also assist with data verification, initial request evaluation, and document collection, allowing employees to focus on more complex tasks (Song, 2025). When combined with sentiment and behavioral analytics, these tools also help companies monitor customer satisfaction in real time and adjust their services accordingly, reducing dissatisfaction and customer loss (van den Broek-Altenburg, 2019). The data collected are further used to improve processes, identify friction points, and design products that better meet customer needs (Yang, 2024).

Internally, AI supports insurance organizations in areas such as strategic planning, portfolio management, and capital optimization (Bhattacharya, 2025). Through advanced analytics tools, companies can simulate different scenarios, assess the impact of various strategies, and detect risks early across markets, products, and customer segments (Hassani, 2020). In terms of regulatory compliance, AI enables automated transaction monitoring, detection of suspicious patterns linked to illegal financial activities, and adherence to complex regulatory requirements (Allbabidi, 2021). It also strengthens internal control by allowing continuous monitoring and early detection of irregularities that might otherwise go unnoticed (Amerirad, 2023). Combined with data governance frameworks, these capabilities enhance organizational resilience and reduce the risk of operational or regulatory penalties (Al-kfairy, 2024).

AI is also increasingly used in human resource management. It supports recruitment, performance evaluation, and skill development processes (Pan, 2022). Algorithms analyze CVs, data from professional platforms, and evaluation results to improve candidate selection and identify training needs within the workforce (Islam, 2023). In terms of skills development, AI systems help detect current and future competency requirements, supporting the design of training programs that strengthen long-term organizational sustainability (Acosta-Prado, 2024). This shows that AI applications extend beyond technical functions and influence how organizations manage knowledge, employees, and innovation (Hržica, 2025).

Finally, the emergence of generative AI has introduced new possibilities for producing texts, contracts, reports, and communication materials. This increases the speed of document creation, supports content adaptation, and enables more personalized communication with customers (Al-kfairy, 2025). As a result, companies are exploring how to integrate these tools in ways that improve efficiency while maintaining quality and regulatory compliance (Al-kfairy, 2024). AI is also used to analyze scenarios and support managerial decisions, such as evaluating the impact of new products, regulatory changes, or macroeconomic shocks (Sánchez, 2025). Overall, the wide range and complexity of AI applications show that its effective use depends on the combined alignment of technical, organizational, regulatory, and human factors (Mpanza, 2025).

2.5 Theoretical models of technology adoption

To examine AI adoption in the insurance industry, it is necessary to first outline the theoretical background that explains how users and organizations form their attitudes and intentions toward such systems. In this context, three key models have had a strong influence: the Technology Acceptance Model (TAM), the Technological–Organizational–Environmental (TOE) framework, and the Unified Theory of Acceptance and Use of Technology (UTAUT). Together, these models provide complementary perspectives on how technology adoption takes place.

Starting with TAM, it was originally developed in the field of information systems to explain why users accept or reject new technologies. The model focuses mainly on perceived usefulness and perceived ease of use (Xue, 2026). Its core assumption is that the more users believe a system improves their performance and is easy to use, the more likely

they are to develop positive attitudes toward it (Ibrahim, 2025). Over time, later versions of the model have introduced additional variables, including subjective norms, trust, and ethical concerns. These factors become especially important when examining complex and less transparent systems (Mustofa, 2025). Research shows that incorporating trust and perceived fairness improves the model's ability to explain user behavior, particularly in contexts where technologies are used to support important decisions (Kim, 2024). As a result, TAM has evolved from a tool for studying simple information systems into a broader framework for understanding how individuals respond to technologies that affect their roles and professional identity (Song, 2025). In the insurance sector, this model helps explain how professionals evaluate the added value of AI and how it influences their daily tasks, which are key elements for successful implementation (Horvey, 2025). At the same time, its focus on intention and usage behavior provides a clear link between system characteristics and actual user actions (Acosta-Enríquez, 2024). Despite its limitations, TAM remains widely used due to its simplicity and ease of application (Xue, 2026).

However, although TAM is useful, it has been criticized for not fully considering organizational and environmental factors. This limitation is particularly important in competitive sectors such as insurance (Sánchez, 2025). To address this gap, the TOE framework is often applied. This framework focuses on the adoption of technological innovations at the organizational level (Mpanza & Mutambara, 2025). It views technology as a set of characteristics, including relative advantage, complexity, and compatibility, which influence how attractive an innovation appears to an organization (Badghish, 2024). The organizational dimension includes structural and cultural factors such as firm size, available resources, management support, and the presence of an innovation-oriented strategy (Hradecký, 2022). The environmental dimension, on the other hand, covers external pressures such as competition, regulatory requirements, customer expectations, and the overall level of technological maturity in the market (Zhou, 2023). In the case of AI, this framework helps explain how technological benefits and risks, organizational capabilities, and external pressures interact to shape adoption decisions within insurance companies (Badghish, 2024). Studies, especially in small and medium-sized enterprises, show that having a clear AI strategy, investing in skills, and accessing external expertise are critical for successful adoption (Sánchez, 2025). At the same time, pressures from competition, customers, and regulation can either encourage or hinder adoption, depending

on how they are interpreted by decision-makers (Mpanza, 2025). The TOE framework is particularly relevant in sectors like insurance, where adoption decisions affect portfolios and require investments in infrastructure and process changes (Atlasi, 2025). It also allows technology adoption to be linked with sustainability, strategic positioning, and long-term competitive advantage (Acosta-Prado, 2024).

UTAUT was developed as an effort to combine and extend several earlier models, including TAM, as well as theories related to social influence and behavioral intention (Xue, 2024). The model introduces four main factors: performance expectancy, effort expectancy, social influence, and facilitating conditions, all of which affect the intention to use technology (Aysan, 2024). Later versions also include variables such as hedonic motivation, price value, and habits, aiming to better capture user experience (Acosta-Enríquez, 2024). UTAUT highlights the role of social norms and expectations from important others, showing that technology adoption is not only an individual cognitive process but also a socially embedded practice (Kim, 2024). In the context of AI, the model helps examine how employees perceive the impact of systems on their performance, the effort required to learn them, and the expectations from managers and colleagues regarding their use (Islam, 2023). Facilitating conditions also play a key role, as they refer to the availability of training, technical support, and adequate infrastructure, which help bridge the gap between intention and actual use (Hržica, 2025). Research suggests that when applying UTAUT to AI, additional factors such as ethics, trust, and perceived risk should be included (Mustofa, 2025). These are especially important given that AI systems often handle sensitive data, influence significant decisions, and replace traditional practices (Al-kfairy, 2024). Another advantage of UTAUT is its flexibility, as it allows differences across user groups to be examined, including demographic and professional characteristics that can influence adoption behavior (Xue, 2026). This makes it possible to identify groups that may be more resistant or more open to AI, which is useful for designing targeted change strategies (Pan, 2022).

Overall, combining these three models allows AI adoption in the insurance industry to be understood at multiple levels. TAM and UTAUT focus mainly on the individual level, explaining how beliefs, attitudes, and social influences shape intention and actual use (Ibrahim, 2025). In contrast, the TOE framework addresses organizational and environmental factors, such as structures, strategic priorities, and external pressures, which

determine whether individual intentions can lead to actual adoption (Mpanza & Mutambara, 2025). Given that AI adoption in the insurance sector affects processes, roles, and relationships with customers, integrating these perspectives provides a more complete understanding. This combined approach makes it possible to identify technological, organizational, environmental, and human factors and to develop a comprehensive theoretical framework.

2.6 Factors influencing the adoption of new technologies in the insurance sector

2.6.1 Technological Factors

Technological factors refer to the inherent characteristics of AI solutions that influence how insurance companies perceive them in terms of usefulness, maturity, and practical applicability (Bhattacharya, 2025). These factors mainly relate to the scope and capabilities of the applications. At the same time, they include issues such as security, data protection, and the technical integration of AI into existing information systems (Hassani, 2020). Understanding these dimensions is essential, as it shapes how management evaluates both the added value that AI can offer and the potential risks associated with its adoption (Sánchez et al., 2025).

Scope and potential of AI

The scope and potential of AI in the insurance industry are linked to its ability to support a wide range of functions, from risk assessment to the development of new business models (Aleksandrova et al., 2023). In this context, modern platforms make it possible to use data at scale for predictive modeling, portfolio segmentation, and the design of personalized products. This has led to a growing strategic interest in the technology (Atlasi et al., 2025).

In addition, AI can automate complex processes such as claims management and fraud detection. This reduces operational costs and allows organizations to respond more quickly to customers (Amerirad et al., 2023). As mentioned earlier, the development of generative AI has further expanded its use to tasks such as producing texts, contracts, and reports, improving the efficiency of administrative and legal processes (AI-kfairy, 2025).

Moreover, due to the flexibility of algorithms and the diversity of insurance areas, including health, motor, and property, it is possible to develop integrated platforms that provide a unified view of risk across the organization (Hanafy & Ming, 2021). Research also shows that when management clearly understands the operational benefits and potential applications of AI, it is more willing to invest in infrastructure and workforce development related to these technologies (Badghish & Soomro, 2024). Therefore, the scope and potential of AI have a dual role: they act both as drivers of innovation and as sources of risk that require careful strategic decisions.

Data security and privacy

Data security and protection are critical technological factors, especially since organizations in the insurance sector handle sensitive information related to individuals' health, financial status, and behavior (Ramezani-a et al., 2025). The large volume of data collected and processed through algorithms has increased concerns about data breaches, unauthorized access, and the possibility that data may be used beyond its original purpose (Allbabidi, 2021).

From a technological perspective, ensuring secure system operation and compliance with regulations requires the use of strong mechanisms such as encryption, access controls, and data anonymization (Amerirad et al., 2023). At the same time, issues related to algorithm transparency remain important. In many cases, it is difficult to understand how models process data, which can increase the sense of opacity and reduce user trust (Owens et al., 2022).

Furthermore, the use of data from multiple sources, such as telematics devices or social media, raises concerns about user consent, the proportionality of data processing, and the limits of acceptable use (Cevolini & Esposito, 2020). As a result, management does not view AI only from a technical perspective, but also as a potential source of vulnerability. Even a single data breach can seriously affect an organization's reputation and financial position (Islam et al., 2023).

For this reason, it is essential to establish mature data governance frameworks and clear policies regarding data access. These measures can positively influence the intention to adopt AI by reducing uncertainty related to security risks (Hradecký et al., 2022). If such

safeguards are not in place, concerns about regulatory penalties, legal claims, and loss of customer trust become stronger. These concerns can act as barriers to adoption, even when the value of AI solutions is recognized (Al-kfairy et al., 2024). Therefore, decisions related to security and privacy are not neutral. They directly affect how willing insurance companies are to invest in AI and integrate it into their core operations (Amerirad et al., 2023).

Compatibility with existing systems

A key factor in this context is the extent to which AI solutions are compatible with existing systems. This is particularly important because companies in the insurance sector operate with a mix of legacy infrastructures and newer platforms (Hassani, 2020). In this setting, AI needs to connect effectively with systems used for contract management, claims handling, and regulatory reporting, while at the same time being introduced without disrupting critical business processes (Pugnetti & Seitz, 2021).

At the technical level, issues such as interoperability, as well as the quality and structure of data, have a direct impact on both the cost and the time required to implement AI projects (Ejiyi et al., 2022). In organizations that rely heavily on older systems, limited compatibility often leads to the creation of parallel structures. This increases system complexity and places additional pressure on IT teams (Allbabidi, 2021).

Compatibility, however, is not limited to system connections. It also *αποφά* the ability of AI systems to produce outputs in formats that can be used effectively by existing tools. This allows organizations to avoid fully redesigning their processes (Bhattacharya et al., 2025). At the same time, lack of compatibility can result in projects that require extensive data transformations, greater human involvement, and higher operational risks. These challenges further discourage investment in AI (Sánchez et al., 2025). For this reason, assessing compatibility with existing systems is critical, as it strongly influences the intention to adopt AI.

2.6.2 Organizational Factors

Organizational factors refer to the internal characteristics of an insurance company that shape the environment in which AI is designed, implemented, and evaluated in terms of its adoption (Sánchez et al., 2025). These factors include underlying cultural assumptions and

strategic priorities, as well as how leadership approaches change and whether the organization invests in developing relevant skills (Hržica et al., 2025). Overall, they influence how projects are structured, how long implementation takes, and how effectively changes are absorbed within the organization (Hradecký et al., 2022).

Organizational culture and strategy

Organizational culture plays a key role in shaping how employees perceive innovation, experimentation, and their willingness to accept risk when adopting advanced technologies (Mpanza & Mutambara, 2025). In insurance environments, where cultures often emphasize compliance, standardization, and error avoidance, AI may initially be seen as a threat that could disrupt stability and control (Cevolini & Esposito, 2020). In contrast, organizations that promote learning, transparency, and collaboration are more likely to view AI as an opportunity to improve existing processes and create new forms of value (Acosta-Prado et al., 2024).

In addition, the presence of a clear digital transformation strategy, where AI is explicitly integrated into long-term objectives, helps ensure that related projects are not treated as isolated technical initiatives. Instead, they are understood as part of broader organizational change (Bhattacharya et al., 2025). This aspect is also closely linked to the willingness to invest in both employees and infrastructure. Organizations that recognize AI as a key driver of competitive advantage are generally more prepared to allocate the necessary resources (Badghish & Soomro, 2024). Empirical evidence shows that when there is no clear AI strategy, initiatives tend to be fragmented and rarely scale effectively (Sánchez et al., 2025). By contrast, when strategy aligns with organizational culture and supports innovation, AI adoption becomes a collective effort, with employees actively participating in the transformation process (Islam et al., 2023).

Management support and leadership

In addition to the factors discussed above, support from top management is equally important, as it directly influences the allocation of resources and the prioritization of specific projects (Hradecký et al., 2022). In insurance organizations, where investment decisions are closely tied to strict control and supervision, a clear position from management on AI adoption sends a strong signal to the entire organization (Bhattacharya et al., 2025).

When leaders understand both the capabilities and the limitations of AI systems, they are more likely to set realistic expectations. This helps avoid both excessive and unjustified optimism, as well as defensive rejection of the technology (Al-kfairy, 2025). In addition, when executives are actively involved in managing AI projects, through committees, accountability structures, and transparent decision-making processes, this strengthens trust and reduces uncertainty related to change (Al-kfairy et al., 2024). Leaders who can connect technical teams, analysts, business executives, and front-line employees also play an important role in aligning different perspectives, priorities, and timeframes (Acosta-Prado et al., 2024).

On the other hand, leadership styles that impose technological solutions without open discussion tend to have negative effects. They often increase resistance, especially when existing professional roles and established decision-making criteria are challenged (Pan et al., 2022). Finally, management support is also reflected in the willingness of leaders to take responsibility for potential errors, particularly in the early stages of implementation. This reduces employee anxiety and encourages a more open approach to experimentation (Mustofa et al., 2025).

Training and Skill Development

Training and skills development are central factors in the organizational context. Their importance lies in the fact that AI adoption requires professionals who can understand both the technical characteristics of these systems and their operational implications (Acosta-Prado et al., 2024). This means that employees involved in pricing, risk management, and front-line activities need to be familiar with key concepts, such as the limitations of algorithms and the potential for bias (Bhattacharya et al., 2025). Research shows that organizations that invest continuously in employee training, covering both technical and ethical aspects, tend to build higher levels of trust and acceptance toward AI (Ramezani-a et al., 2025).

At the same time, skills development is not limited to highly specialized technical expertise. It also includes broader capabilities that allow employees to critically interpret and evaluate the outputs produced by algorithms (Ibrahim et al., 2025). In this context, the formation of cross-functional teams is essential, as it supports collaboration, knowledge sharing, and mutual learning (Ejiyi et al., 2022). When such skills are lacking, this is

identified in the literature as a major barrier to the wider adoption of AI (Sánchez et al., 2025).

Finally, training is closely linked to the psychological dimension of adoption. Programs should clearly highlight the benefits and possibilities of AI, presenting it as a tool that supports rather than replaces human roles. This approach helps strengthen acceptance and reduces concerns related to job displacement (Acosta-Enríquez et al., 2024).

2.6.3 External Environmental Factors

External environmental factors describe the conditions that exist outside the insurance company (Sánchez et al., 2025). These include the legal and regulatory framework, the broader economic environment, and the trends shaping the market and competition. Together, they define the limits and opportunities within which organizations operate (Mpanza & Mutambara, 2025).

Legal and regulatory framework

The legal and regulatory framework sets the rules for how data can be used, the level of transparency required in algorithms, and the accountability obligations of insurance companies (Allbabidi, 2021). In this context, regulations that focus on personal data protection and provide guidance for these systems make it necessary for AI projects to address compliance requirements from the design stage (Ramezani-a et al., 2025).

At the same time, as attention to issues such as algorithmic bias and fairness increases, there is a growing need to choose technologies that offer explainable results and allow proper model evaluation (Owens et al., 2022).

In addition, existing risk management regulations require clear structures for overseeing data and models. This highlights the importance of having well-developed governance processes before AI can be widely implemented (Bhattacharya et al., 2025). Finally, when there is uncertainty about how regulations may evolve, organizations often prefer to test AI through pilot projects rather than proceed with full-scale adoption (Al-kfairy et al., 2024).

Economic factors

In addition to the factors mentioned above, the economic environment has a strong influence on the resources available for AI investments, as well as on how organizations

perceive investment risk (Badghish & Soomro, 2024). During periods of limited profitability or stricter solvency requirements, companies tend to assess such projects more carefully. In these cases, they often prefer solutions that deliver quick and measurable results (Hradecký et al., 2022).

At the same time, the need to improve efficiency and reduce operating costs increases the appeal of AI. Its applications support the automation of repetitive tasks and improve accuracy in risk assessment (Hassani et al., 2020).

Macroeconomic changes can also create opportunities. They allow organizations to use algorithm-based tools to adjust pricing quickly, based on new market data (Atlasi et al., 2025). However, when an organization lacks resilience to economic shocks, it tends to be more cautious with complex technology investments. This caution is linked to concerns about possible failures or delays in achieving returns (Islam et al., 2023).

Market trends and competition

Market trends and the intensity of competition are also important external factors. Their influence becomes stronger when customers compare the quality of digital services and overall experience across providers (Sánchez et al., 2025). In this environment, established companies are pushed to upgrade their infrastructure in order to remain flexible. At the same time, they aim to strengthen their forecasting capabilities so they can maintain their market share (Bhattacharya et al., 2025).

Monitoring developments in related sectors, such as banking and auditing, also plays a role. Insurance companies often follow strategies based on imitation, adopting technologies that have already been tested in other parts of the market (Allbabidi, 2021). In addition, the growing availability of cloud infrastructure and ready-to-use algorithmic services makes it easier to adopt advanced systems. This reduces technical barriers and allows new players to enter the market more easily (Mpanza, 2025).

2.6.4 Human/ Person Related Factors

Human factors relate to the attitudes, emotions, and motivations that employees have toward AI (Song et al., 2025). They are not limited to knowledge of technology, but also involve how this knowledge connects to daily work, as well as to employees' sense of autonomy and professional identity (Islam et al., 2023). Understanding these aspects helps

explain why similar AI solutions may be welcomed with enthusiasm in some departments, while in others they lead to hesitation or resistance (Xue et al., 2026).

Employee perceptions and attitudes towards AI

A key factor that shapes acceptance is the way employees perceive and interpret AI. These perceptions play a central role in whether technology is seen as supportive or as a threat to their role (Ibrahim et al., 2025). Positive attitudes are more likely to develop when AI is understood as a tool that reduces routine tasks, supports evidence-based decisions, and improves service quality (Song et al., 2025). In contrast, when employees believe that algorithms are introduced for control, monitoring, or replacement of human work, feelings of anxiety and distance tend to emerge (Islam et al., 2023).

In the insurance sector, professional identity is closely tied to risk assessment. For this reason, employees may perceive AI models as a threat that weakens their expertise and role within the organization (Cevolini & Esposito, 2020). Clear and open communication about the goals, benefits, and limitations of AI can help address these concerns. It supports the formation of more positive attitudes and encourages acceptance (Acosta-Prado et al., 2024).

Experience and knowledge in AI

Previous experience and knowledge also play an important role, as they shape how individuals understand the benefits and limits of AI tools (Mustofa et al., 2025). Those who have already been exposed to AI in education or work tend to form more realistic expectations and show a greater willingness to experiment (Xue et al., 2024). In contrast, when such experience is missing, people may either accept results without questioning them or reject the models entirely. This often happens because they do not clearly understand how predictions are produced or what their limitations are (Ibrahim et al., 2025).

For this reason, targeted training is essential. It should include practical examples from the insurance sector and encourage discussion based on real cases. This approach helps employees move from abstract ideas about AI to a clearer and more concrete understanding (Owens et al., 2022). As a result, experience and knowledge should not be

seen as fixed individual traits. Instead, they are organizational resources that can be developed through proper training and active involvement in AI-related projects (Allbabidi, 2021).

Response to change

A key aspect to consider is how employees respond to change. This reflects how willing they are to question established practices and try new ways of organizing their work (Pan et al., 2022).

Employees who are strongly oriented toward learning tend to view pilot projects as opportunities for development. In many cases, they take on the role of technology ambassadors and help connect technical teams with the rest of the organization (Acosta-Enríquez et al., 2024).

At the same time, past experiences with digital transformation initiatives can sometimes lead to fatigue. This may result in resistance, even when there is formal acceptance of change (Islam et al., 2023). For this reason, it is important to introduce innovations in a way that avoids disruption. A structured change management approach, with a clear timeline, transparency, opportunities for feedback, and gradual implementation, can support smoother adoption (Hradecký et al., 2022).

Trust in AI and its results

Trust in AI is a key psychological factor that connects knowledge of the technology with the willingness to use it in practice (Gramegna & Giudici, 2020). Trust tends to grow when models show consistent results, have been tested with real data, and are supported by clear explanations. This helps users understand the main factors behind each decision (Owens et al., 2022).

At the same time, acceptance is stronger when employees feel they have the final say and can question or adjust algorithmic suggestions. This preserves their sense of responsibility and autonomy (Cevolini & Esposito, 2020). On the other hand, if earlier AI projects were linked to unclear outcomes or errors, trust can weaken. This, in turn, reduces the willingness to engage with similar initiatives in the future (Sánchez et al., 2025).

Personal and professional development through AI

Personal and professional development is an important driver of acceptance. This is especially true when employees feel that working with AI strengthens, rather than weakens, their professional profile (Acosta-Prado et al., 2024). Participation in interdisciplinary teams also supports this process, as it brings together expertise from actuarial science, data analysis, and business strategy. In this way, employees can build confidence and gain recognition within the organization (Bhattacharya et al., 2025).

In addition, when AI projects are clearly linked to career development, with new roles and certification opportunities, employees are more willing to invest time in learning these tools, testing them, and taking on extra responsibilities (Mpanza & Mutambara, 2025). Examples include the creation of roles such as AI coordinators and data specialists with strong knowledge of the insurance sector (Horvey et al., 2025). In this context, AI is no longer seen as a tool that simply supports processes. It becomes part of a broader shift, where professional roles evolve and work in the insurance industry gains new meaning (Yang et al., 2024).

3. Research Methodology

The methodology followed in this study is described in detail in this chapter. In particular, the research design and the key decisions taken (purpose, questions, approach and type of research), the target population and the characteristics of the sample, the research tool used.) are presented. It also presents the data collection process, the ethical and ethical issues examined, the methods of data analysis, as well as the evaluation of the reliability and validity of the study. Finally, there is a discussion about the limitations of research.

3.1 Research Design

3.1.1 Purpose of the research

A clear definition of purpose provides the framework within which specific research questions are formulated (Babbie, 2010; Bryman, 2016).

The purpose of this research study was to investigate the factors influencing the adoption of AI in the insurance industry, with an emphasis on the direct and indirect role of technological, organizational, environmental and human factors. At the same time, the research aims to examine the role of human factors as a mediation mechanism, as well as to assess whether the adoption of AI affects organizational efficiency and service delivery.

3.1.2 Research Questions-Hypotheses

The main research question is, how technological, organizational, environmental and human factors directly and indirectly influence the adoption of AI in the insurance industry and what is the impact of this adoption on organizational efficiency and quality of services?

Specific Research Questions

1. What are the perceptions of insurance company employees regarding the technological, organizational, environmental, and human factors associated with AI adoption?
2. What are the correlations between technological, organizational, environmental, and human factors and the intention to adopt AI?
3. To what extent do technological factors influence the adoption of AI, directly and/or indirectly through human factors?

4. How do organizational factors influence AI adoption, and to what extent is their influence mediated by human factors?
5. How do environmental factors influence AI adoption, and what is the indirect role of human factors?
6. What is the direct role of human factors in shaping AI adoption intention?
7. Do human factors mediate the relationship between technological, organizational, and environmental factors and the adoption of AI?
8. Do technological, organizational, or environmental factors modify the relationship between human factors and AI adoption?
9. To what extent are the demographic and professional characteristics of the participants related to the intention to adopt AI?

3.1.3 Research approach

This study follows a quantitative research approach, as it seeks to systematically capture employee perceptions about the adoption of AI and to examine the relationships between specific factors associated with it. The quantitative approach was considered the most appropriate, because it allows the measurement of attitudes, perceptions and intentions through standardized questions, but also the statistical investigation of the intensity and direction of the relationships between the research variables (Babbie, 2010; Bryman, 2016).

This choice is directly linked to the nature of the research questions. This research is not limited to a descriptive depiction of opinions, but seeks to investigate whether technological, organizational, environmental and human factors are related to the intention to adopt AI and to what extent some of them act directly, indirectly or modifying. For this reason, it was necessary to use an approach that allows for hypothesis testing and the application of inductive statistical techniques.

At the same time, the quantitative logic of the study is reinforced by the fact that the research tool was organized in clear conceptual dimensions, which emerge from the international literature on the adoption of technologies in organizational environments and in particular in the insurance industry. A central point of reference was the Technology–Organization–Environment (TOE) framework, which has been used extensively in technology adoption studies, while in the present research it was enriched with the human

dimension and with a separate depiction of adoption intention (Gupta et al., 2022; Nguyen et al., 2024).

3.1.4 Type of research

In terms of its type, the research is primary, empirical, non-experimental and cross-sectional. It is primary, because the data were collected directly from the participants for the purposes of the specific study and not from secondary sources. It is empirical, because it is based on real data obtained from employees of insurance companies. It is non-experimental, as there was no intervention or manipulation of the variables by the researcher, But the already formed attitudes and experiences of the participants were recorded. Finally, it is cross-sectional, since the data collection was carried out over a specific period of time and captures a temporal "intersection" of the sample's perceptions (Gray, 2018; Bryman, 2016).

On an analytical level, the study combines descriptive, correlational and interpretative character. It is descriptive because it presents the basic demographic and professional characteristics of the participants and describes their level of agreement on the individual dimensions of the research. Its nature is correlative, because it examines the relationships between the basic variables. Its character is interpretive, because it attempts to explore which factors contribute most to the intention to adopt AI and in what way.

The choice of this design is considered appropriate for research concerning the acceptance and adoption of technologies in organizational environments, where the aim is not only to describe attitudes, but also to investigate the factors that influence them (Gupta et al., 2022; Nguyen et al., 2024).

3.2. Population and Sample

3.2.1 Description of the reference population

The reference population of this survey was the employees of insurance companies operating in the area of Athens, Attica. This population was considered particularly suitable for this study, as employees are the direct users, recipients or even mediators of AI in the work environment. Therefore, their perceptions are critical to understanding the degree of readiness, acceptance, and intent to use such technologies.

The population was not limited to a single hierarchical level or to one functional sector. Instead, it included employees from different positions, such as employees,

supervisors and management executives, as well as people with different levels of experience, education and digital skills. This choice allowed a more complete capture of the adoption of AI as an organizational phenomenon, which depends not only on the technology itself, but also on the way it is perceived by people with different roles within the same industry.

The focus on the region of Attica is justified both by the concentration of a significant number of insurance companies in the wider region, and by the fact that Attica is the main hub of administrative, economic and technological activity in the country. It therefore offers a fertile field for studying trends related to digital transformation and the organizational adoption of innovations.

3.2.2 Sampling method

Sample selection was performed by non-probabilistic convenience sampling, with elements of a network or avalanche approach. This option was considered functional and realistic, as there was no available and complete register of all employees of the target population, while access to participants depended to a large extent on their professional availability and consent. In practice, the questionnaire was circulated electronically to employees of insurance companies and then further communicated through professional networks to enhance the participation of people with similar characteristics.

Although this method does not allow for strict statistical generalization to the population as a whole, it is widely used in field surveys when the population is inaccessible or when the survey requires rapid and practical data collection from real professionals in the field (Bryman, 2016; Gray, 2018). In the present study, sampling was organised in such a way as to ensure the greatest possible heterogeneity in terms of gender, age, work experience, job position and size of the enterprise.

3.2.3 Sample size

The final sample size amounted to 120 employees of insurance companies from the area of Athens, Attica. This magnitude is considered sufficient to apply descriptive and inductive statistical techniques, such as difference checks, correlations, multiple linear regression, as well as mediation and modification analyses, provided that the results are interpreted with due methodological care (Hair et al., 2019; Tabachnick & Fidell, 2013).

At the same time, the sample was considered functionally adequate in relation to the purpose of the survey, as it allowed on the one hand to capture key subgroups of the insurance sector and on the other hand to investigate differences based on demographic

and professional characteristics. However, due to the non-random selection of the sample, the findings should not be considered strictly representative of all employees in the insurance sector in Greece, but primarily indicative of the specific geographical and professional reality.

3.2.4 Inclusion and exclusion criteria

The survey included employees who cumulatively met the following criteria: they were working at the time of the survey in an insurance company operating in the area of Athens, Attica, had an active professional relationship with the company, were adults and voluntarily accepted to participate, after being informed about the purpose and process of the survey.

The study excluded people who did not work in the insurance industry, worked outside the defined geographical area, or did not complete the questionnaire to a degree that would allow it to be used in the analysis. Also, questionnaires with obviously incomplete data or answers that did not allow secure processing, such as cases of systematic non-response or obviously inconsistent completions, were not included. This ensured that the final set of data was sufficient and suitable for the implementation of the statistical analysis.

3.3. Research Tool

The main data collection tool of this research was a structured closed-ended questionnaire, specially designed to capture the perceptions of employees of insurance companies regarding the adoption of AI. The choice of the questionnaire was considered appropriate because it allows the collection of standardized data from a relatively large number of participants, facilitates the comparison of responses and supports the quantitative investigation of relationships between variables (Babbie, 2010; Bryman, 2016).

The rationale for setting up the tool was mainly based on the Technology–Organization–Environment (TOE) framework, which is systematically used in the study of organizational technology adoption, and in particular in research on the adoption of AI applications in the insurance industry (Gupta et al., 2022). However, because this research also focuses on the role of employees themselves as users, recipients and interpreters of technological change, the tool was enriched with a separate unity of human factors, as well as a distinct scale of adoption intent. This choice is consistent with more recent studies highlighting the importance of attitude, perceived utility, usability, perceived risk, and

trust in technology within insurance organizations (Nguyen et al., 2024). In addition, the inclusion of statements concerning efficiency, quality of service, data security, compatibility, trust, and professional development is documented by the literature on the impact of AI on the insurance value chain (Eling et al., 2022).

The questionnaire was organized into six main sections.

The *first section* concerned the demographic and professional characteristics of the participants. It included questions on gender, age, years of work in the insurance industry, level of education, job position, size of the company, previous experience of using AI at work and level of digital skills in ICT. participants. This section served both to describe the sample and to explore possible variations in adoption intention based on the characteristics of the participants.

The *second section* dealt with technological factors and included eight statements. These statements addressed employees' perception of the scope and potential of AI, such as improving performance, reducing errors, improving service quality and automating tasks, and issues such as data security, usability, compatibility with existing systems and its perceived complexity technology. In this way, the basic technological aspects associated with the acceptance of an innovation in the workplace were covered. This section is mainly documented by the technological determinants of the TOE framework, and in particular by the dimensions of relative advantage and complexity, as used in the research of Gupta et al. (2022). At the same time, statements regarding perceived utility, usability, and risk are directly linked to the logic of Nguyen et al. (2024), while the emphasis on data security and process improvement is entirely consistent with Eling et al.'s (2022) discussion of the impact of AI along the insurance value chain. Therefore, this section is not a copy of a single scale, but a bibliographically documented composition of individual constructions, adapted to the environment of insurance companies.

The third section concerned organizational factors and included nine statements. This section reflected issues of organizational culture and strategy, such as whether the adoption of AI is part of the company's strategy, but also issues of administrative support, such as the provision of resources, time, guidance from management and recognition of employees' opinions. At the same time, organizational support in terms of training and skill development around AI was also examined. The theoretical basis of this module is mainly found in the organizational dimensions of the TOE, i.e. the support of top management, the technological readiness and the financial readiness of the organization

(Gupta et al., 2022). In the same article it is explicitly stated that the corresponding organizational items were drawn from previous studies, such as Lai et al. (2018), Wong et al. (2020), Henao Ramírez and López-Zapata (2022) and Martins et al. (2019). In addition, the emphasis on education, technical support and favorable conditions of use is also linked to the concept of facilitating conditions, as reflected in Nguyen et al. (2024).

The *fourth section* dealt with environmental factors and comprised eight statements. These statements covered the institutional and regulatory framework, the impact of data protection regulations, the financial capacity of businesses to invest in AI technologies, as well as external pressures related to competition, maintaining a competitive advantage, social acceptance, customer expectations and technological developments. This section allowed the capture of the wider business and institutional framework in which the adoption decision is made. This section is directly based on the environmental dimensions of the TOE, i.e. market dynamics, regulatory support and competitive pressure, as exploited by Gupta et al. (2022), with the original source mainly the tool of Wong et al. (2020). At the same time, the addition of elements such as data protection requirements, changing customer expectations, and the technological transition of the industry is in line with the literature that highlights that AI is transforming the insurance market at the level of products, service, regulatory compliance, and value ecosystems (Eling et al., 2022).

The *fifth section* concerned human factors and included fourteen statements. It reflected the attitudes and perceptions of employees towards AI, their willingness to learn, their enthusiasm for its potential, the weighing of benefits and risks, their level of knowledge and experience, the need for additional training, their comfort in the face of change, fears of job substitution, trust in AI results, as well as the perception that AI can contribute to professional growth and improved work experience. This section was particularly important, as it corresponded to the core of the theoretical extension of research beyond the classical TOE model. This section has the closest correspondence with the model of Nguyen et al. (2024), which is organized around the concepts of perceived risk, perceived self-efficacy, facilitating conditions, perceived ease of use, perceived usefulness and attitudes toward adoption. On a more analytical level, the emphasis on user self-efficacy and self-confidence is based on the relevant literature of Kulviwat et al. (2014) and Li et al. (2022), while the relationship between usability, utility and positive attitude towards AI has already been documented by Chen et al. (2022) and

Na et al. (2023). Also, concerns about perceived risk and safety are consistent with the findings of Horowitz and Kahn (2021). Of particular importance is that some statements of human unity, such as those concerning trust in the results of AI, its contribution to better decision-making, professional development and improvement of the work experience, are not mere metaphors of a single tool, but bibliographically plausible and thematically powerful adaptations. Their documentation results from studies showing that trust enhances the intention to use AI insurance applications and that AI is linked to increased productivity, reduced operational costs, and a reshuffle of roles towards more complex and creative tasks (Pham et al., 2022; Eling et al., 2022). In the same way, statements about possible replacement of certain tasks or fears of job losses are not drawn from an autonomous, ready-made insurance subscale, but are adequately documented by the literature describing the automation of standardized procedures and the transformation of work in the insurance industry (Gupta et al., 2022; Eling et al., 2022).

The *sixth section* concerned the intention to adopt AI and included seven statements. These statements explored the intention to start using AI tools immediately, their systematic use in the near future, the willingness to adopt new technologies when they become available, the expectation of increasing use over time, the intention to actively use when the organization makes such tools available, the integration of AI into daily work and the overall adoption intention based on the expected benefits. This particular section is most directly grounded in the behavioral intention scales used by both Gupta et al. (2022) and Nguyen et al. (2024). In these two studies, the intent is reflected in statements regarding the prediction of the adoption of AI by the organization, the personal intention of future use and the desire to use the technology in specific work functions.

In total, the questionnaire included 46 scale statements and a set of demographic and occupational questions. The statements of the key modules were formulated in a clear, direct and workplace-oriented manner of insurance companies, so that they could be understood by participants with different levels of knowledge and experience.

A five-point Likert scale was used to measure attitudes and perceptions (1=Strongly disagree, 2=Disagree, 3=Neither agree nor disagree, 4=Agree, 5=Strongly agree). The Likert scale is one of the most commonly used techniques in the social sciences, because it allows the quantification of subjective attitudes in an easy-to-use and analytically usable way (Bryman, 2016). The choice of a five-level format was considered

appropriate because it offers sufficient gradation, without burdening the participants cognitively.

Pilot implementation

Prior to the wide distribution of the questionnaire, a small-scale pilot application (8 participants) was carried out to test the clarity of the wordings, the logical sequence of the questions, the understanding of AI-related terms and the total completion time. This pilot process was of particular importance, as the tool combined technological, organizational, environmental and human dimensions, which had to be rendered in an accurate and understandable way for employees of different specialties.

Based on the observations of the pilot, small improvements were made to the wording of some questions and the overall structure of the questionnaire to enhance readability and reduce possible ambiguities. The use of a pilot application is considered a key step in enhancing the clarity and content adequacy of a research tool, especially when it has been adapted to a specific organizational and sectoral context (Gupta et al., 2022; Nguyen et al., 2024).

3.4. Data Collection Process

The data collection took place during the period from January to March 2026. For the implementation of the survey, the digital platform Google Forms was used, through which the questionnaire was created and distributed in electronic form. The option of electronic filling was considered appropriate because it facilitated the access of employees with demanding professional schedules, reduced the time for data collection and supported the immediate recording and organization of responses.

The distribution of the questionnaire was carried out through professional contacts and networks related to the insurance industry in the region of Attica. In the introductory part of the questionnaire there was a short informative text on the purpose of the survey, the duration of completion, the voluntary nature of the participation and the assurance of anonymity of the answers. The participants completed the questionnaire individually and in person, without the intervention of the researcher during the response process. After the completion of the collection, the answers were checked for completeness and suitability for statistical processing. This process resulted in the final set of 120 valid questionnaires, which was used in the analysis.

3.5. Ethics and Ethics Issues

This research was conducted with respect to the basic principles of research ethics and ethics. The first and foremost principle was voluntary participation. No employee was obliged to take part, and all participants were informed from the outset about the purpose of the study, the content of the questionnaire and the academic nature of the research.

Equally important was ensuring anonymity and confidentiality. No data was collected that could lead to a direct identification of the participants, such as name, employee registration number or specific corporate identity. The data were used exclusively for research purposes and are presented only in aggregated form, so that it is not possible to identify individual persons or companies.

Particular attention was also paid to data protection. The research files were kept in a secure digital environment and access to them was restricted exclusively to the researcher. At the same time, it was emphasized to the participants that they had the right to stop filling at any time, without any consequences.

Finally, the questions were formulated in a way that avoided offensive, pressuring or stigmatizing content. While some statements addressed concerns about job losses, data security, or trust in AI, their wording remained neutral and research-based to serve the purpose of the study without causing unnecessary psychological distress.

3.6. Data Analysis Methods

The analysis of the data was performed using the IBM SPSS Statistics statistical package, version 29 and the use of the PROCESS macro which can also be integrated into SPSS. In the first stage, the coding and checking of the data in terms of their completeness and consistency preceded. Descriptive statistical measures were then calculated for all survey variables. For categorical variables, frequencies and percentages were calculated, while for scales and individual statements, averages and standard deviations were calculated. For the composite indicators of the key factors, the average of the corresponding declarations was used.

Prior to the application of inductive statistical techniques, the regularity of distributions was checked by means of skewness and kurtosis. This control is crucial because it allows for the selection of appropriate statistical tests and enhances the validity of the conclusions. In the present study, the values of skewness were found within acceptable limits, while most of the values of curvature were at satisfactory levels. Despite

the increased curvature in a single variable, the deviation was considered tolerable, given the sample size and the relative resistance of the parametric methods to mild deviations from the normal (Field, 2018; Hair et al., 2019; Kim, 2013; Tabachnick & Fidell, 2013).

In a subsequent step, differences checks were implemented to investigate potential variations in AI adoption intention based on demographic and occupational characteristics. For dichotomous variables, the t-control was used for independent samples, while for variables with more than two categories, one-way ANOVA analysis was used. Where statistically significant differences occurred, subsequent Tukey comparisons followed to identify the groups between which the differentiation occurred. In the controls of two groups, effect sizes were also calculated, so that the interpretation is not limited only to statistical significance but also takes into account the practical significance of the differences (Cohen et al., 2003).

To investigate the relationship between key factors and adoption intention, the Pearson correlation coefficient was used. Pearson's choice was considered appropriate, as the variables were derived from Likert-type scales that were used as composite indicators and tested for their distribution. This analysis made it possible to assess the direction and intensity of the relationships between technological, organisational, environmental and human factors and the intention to adopt.

Multiple linear regression was then applied with the Enter method in order to investigate the net contribution of each key factor in predicting AI adoption intent. This method was chosen because the independent variables had been determined theoretically and corresponded to clear research hypotheses. In this way, it was possible to estimate the effect of each factor, while controlling for the effect of the others (Meyers et al., 2013; Tabachnick & Fidell, 2013). In the context of the same model, the basic assumptions of regression were tested, such as polylinearity through tolerance and VIF indices, residue independence through the Durbin–Watson index, as well as residue normality through histogram and normal probability diagram.

Beyond direct relationships, the analysis also extended to the investigation of indirect and modifying effects. In particular, mediation analysis using the PROCESS process and Model 4 was applied to control mediation, where the role of human factors as mediators in the relationship between technological, organizational and environmental factors and adoption intention was examined (Hayes, 2022; Preacher & Hayes, 2008). To control the modifying effect, moderation analysis was applied using PROCESS Model 1 to

examine whether technological, organizational or environmental factors strengthen or weaken the relationship between human factors and adoption intention. In these analyses, the interpretation was based on factor values, significance levels, and bootstrap confidence intervals (Hayes, 2018; Field, 2018).

For all statistical tests the significance level was set at $p < .05$. This option is in line with standard practice in the social sciences and allows for a balanced interpretation of the results.

3.7. Conceptual Validity

The conceptual validity of the present research concerns the extent to which the research tool adequately and clearly captures the theoretical concepts it attempts to measure. In the present study, the conceptual validity is primarily reinforced by the close connection between the theoretical framework, the research questions and the structure of the questionnaire. The key variables of the survey were not selected piecemeal, but were organized around a coherent scheme that includes technological, organizational, environmental, and human factors, as well as adoption intent as a dependent variable. With this arrangement, the tool directly corresponds to the content of the hypotheses and research questions of the study (Gupta et al., 2022; Nguyen et al., 2024).

In particular, the technological factors were defined in a way that addresses both the perceived utility and functional capabilities of AI as well as critical issues such as data security, compatibility with existing systems, and complexity. The organizational dimension was captured through elements of strategy, culture, administrative support and training. The environmental dimension covered the institutional framework, regulatory requirements, financial investment capacity, competitive conditions and external market pressures. The human dimension included attitudes, perceptions, level of knowledge, adaptation to change, confidence and perception of professional development. Finally, adoption intent was measured with statements that capture the future mood of use, the systematization of utilization, and the readiness to integrate AI into daily work. This correspondence between theoretical concept and questions substantially enhances the conceptual adequacy of the tool.

The conceptual validity is further strengthened by the fact that the statements of the questionnaire were based on established bibliographic approaches and adapted to the specific environment of the insurance market. This adaptation was crucial because the

adoption of AI in the insurance industry is not only about the technical operation of systems, but also about how they affect day-to-day work, quality of service, risk management, regulatory compliance, and employee and customer trust (Eling et al., 2022).

Indications in favor of conceptual coherence also emerge from the model of the findings. Most scales showed high internal consistency, suggesting that the individual questions of each unit revolve around a common conceptual core. In particular, organizational, environmental, human factors and adoption intention showed satisfactory to very high reliability. The lower alpha value in the technological dimension does not necessarily negate its conceptual validity, but rather indicates that it is a broader and more complex concept, in which individual aspects, such as utility, security, compatibility and complexity, coexist. In other words, this scale seems to capture a multidimensional reality, which needs careful interpretation. Overall, it can be argued that the tool has satisfactory conceptual validity, as the individual modules correspond to the theoretical concepts sought to be measured and are consistently linked to the research model of the study.

4. Results and Discussion

4.1. Introduction

This chapter presents the findings of the empirical study and provides answers to the research questions formulated in the previous chapter. The analyses aim to explore employees' perceptions of the factors associated with Artificial Intelligence (AI) adoption and to examine the extent to which these factors shape their intention to adopt AI within the insurance sector.

The chapter is organized in a stepwise manner, following the logic of the research design. It begins with a description of the demographic and professional characteristics of the participants, together with the assessment of the reliability of the measurement scales. Descriptive statistics are then presented to provide an overview of participants' perceptions regarding the technological, organizational, environmental, and human factors associated with AI adoption, as well as their intention to adopt AI.

Subsequently, inferential statistical analyses are conducted to examine the relationships among the study variables and to test the proposed research questions. Correlation analysis is first employed to explore the associations between the main constructs. Multiple linear regression analysis is then used to identify the factors that directly predict AI adoption intention. To obtain a more comprehensive understanding of these relationships, mediation and moderation analyses are performed to examine the role of human factors in the relationships between technological, organizational, and environmental factors and AI adoption intention.

Finally, the chapter investigates whether employees' intention to adopt AI differs according to their demographic and professional characteristics. Taken together, these analyses provide a comprehensive understanding of the mechanisms underlying AI adoption in the insurance industry and establish the empirical basis for the interpretation and discussion of the findings presented in the following chapter.

4.2. Sample description

Regarding the demographic and occupational characteristics of the 120 participants (Table 2), in terms of gender, women appear more (69, 57.5%) than men (51, 42.5%). This

finding suggests that the industry has a strong female participation, which is likely linked to the nature of administrative and service roles.

Regarding the age distribution, it shows concentration in productive ages. The largest group is 25–34 years old (49, 40.8%), followed by the 35–44 group (32, 26.7%). Employees aged 45–54 are fewer (18, 15.0%) and over 55 (17, 14.2%). Those under 25 are very few (4, 3.3%). This shows a limited entry of very young workers and an industry that relies on more mature human resources.

In terms of professional experience, almost half have more than 10 years in the industry (59, 49.2%). This is followed by those with 1–5 years of experience (41, 34.2%), while smaller percentages are recorded for 6–10 years (14, 11.7%) and less than 1 year (6, 5.0%). This element shows a combination of experience and renewal, but with a clear superiority of the more experienced.

The level of education is particularly high. Most of them have a university degree (50, 41.7%) or a master's degree (50, 41.7%). On the contrary, very few have secondary education (5, 4.2%) or vocational training at IEK (6, 5.0%), while very few have a doctorate (2, 1.7%). This suggests that the discipline requires high cognitive specialization and theoretical training.

In terms of jobs, the majority are employees (79, 65.8%), while fewer are supervisors (24, 20.0%) and even fewer are directors or deputy directors (17, 14.2%). This distribution is expected, but it also shows a relatively pyramidal structure with limited positions of responsibility.

In terms of business size, most of them belong to the 1-100 employee category (67, 55.8%). This is followed by companies with 401–1000 employees (22, 18.3%), while smaller percentages appear in categories 101–400 (16, 13.3%) and over 1000 (15, 12.5%). This indicates a market dominated by smaller organizations, but also by the presence of larger structures.

Of particular interest is the experience with AI. The majority state that they have relevant experience (73, 60.8%), while a significant percentage does not (47, 39.2%). This finding shows that AI has already entered the industry, but not in a uniform way.

Also, digital skills appear mostly at a good level (66, 55.0%). This is followed by basic skills (31, 25.8%), while few say they are excellent (13, 10.8%) or minimal (10, 8.3%). This indicates that there is a satisfactory knowledge base, but not a high level of expertise.

Regarding the use of AI tools (Figure 1) from the sample of 120 participants, given that the participants had multiple choices, a total of 226 responses emerged and based on them the percentages were calculated. The results show that the most popular tools are Open AI (29.2%) and Google AI (28.8%), which garner nearly 60% of the total choices. This suggests that these platforms have a dominant position and high awareness among users. At the same time, the "Other" category also shows a significant percentage (23.5%), which shows that participants also use a wide range of other tools, possibly more specialized or less well-known. In contrast, tools such as Microsoft Research (9.3%) show moderate use, while services such as Google Cloud (3.5%), Human AI/Open AI Gym (2.2%) and Amazon Web Services (1.8%) show very low penetration. This finding may be related to the fact that these tools require more specialized knowledge or are aimed at a more technical audience. Of particular interest is the very low percentage of participants who say they do not use AI tools at all (1.8%). This indicates that AI has already been largely integrated into users' daily practice. Therefore, the data highlights a clear trend of widespread use of AI tools, with the dominance of a few popular platforms but also the simultaneous presence of many alternatives. At the same time, it should be noted that the percentages reflect choices and not unique users, which limits the possibility of direct comparison of the actual penetration of each tool in the population.

Overall, the sample is characterized by a high level of education and significant professional experience. However, the limited presence of very young workers and the modest development of advanced digital skills are critical points. At the same time, the use of AI seems to be increasing, but it has not yet been fully integrated. This suggests that the insurance industry is in a transitional stage, with a need for further education and technological adaptation.

Table 1. *Distribution of Frequencies and Percentages of Demographics- Professional Features*

Gender	Frequency (N)	Percentage (%)
Male	51	42.5
Female	69	57.5
Age		
Under 25	4	3.3

25–34	49	40.8
35–44	32	26.7
45–54	18	15.0
55 and over	17	14.2
How long have you been working in the insurance sector?		
Less than 1 year	6	5.0
1–5 years	41	34.2
6–10 years	14	11.7
Over 10 years	59	49.2
Highest educational qualification		
Secondary Education	5	4.2
Vocational Institute (IEK)	6	5.0
University Degree	50	41.7
Master's	50	41.7
Doctorate	2	1.7
Other	7	5.8
Job position		
Director/Deputy Director	17	14.2
Supervisor	24	20.0
Staff	79	65.8
Number of employees		
1-100	67	55.8
101-400	16	13.3
401-1000	22	18.3
1001 and above	15	12.5
Do you have previous experience using AI at work?		
Yes	73	60.8
No	47	39.2
How would you assess your ICT (Information & Communication Technology) skills?		
Minimal	10	8.3

Basic	31	25.8
Good	66	55.0
Excellent	13	10.8

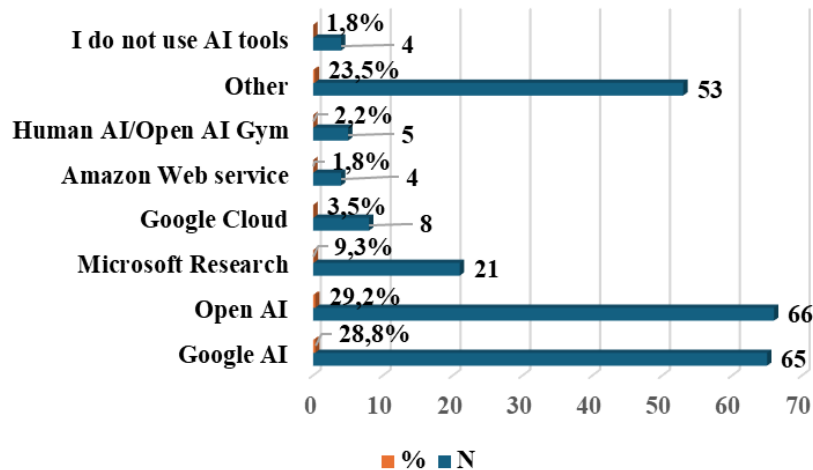


Figure 1. *Use of Artificial Intelligence Tools*

4.3. RQ1: Perceptions regarding the technological, organizational, environmental, and human factors associated with AI adoption

4.3.1. Technological Factors

Regarding the perceptions of the participants on the technological factors related to AI (Table 3), and in particular regarding the Scope and Potential of AI, a generally positive picture is formed. The majority believe that AI can enhance performance at work, with a very high agreement rate (82.5%) and a particularly high average value (AP=4.11 SD=.069). Similarly, the perception of improving the quality of services is positive, with 68.4% expressing agreement (AP=3.78 SD=.080).

However, in more specific modes, the stops appear more restrained. For example, in terms of error reduction, 62.5% agree, but a fairly high percentage remains neutral (28.3%), which is reflected in a lower average value (AP=3.66 SD=.082). A similar picture exists in the automation of daily tasks, where 65.9% express a positive attitude, but reservations remain (AP=3.74 SD=.094). Overall, the benefits of AI are recognized, but not with absolute certainty in all its dimensions.

Regarding Data Security and Privacy, opinions are more divided. About half of the respondents say they are concerned about data security (50% agree/strong agreement),

while 26.7% disagree. The average value (AP=3.36 SD=.105) is near neutral, indicating that the issue of security is a significant consideration and a potential inhibiting factor for the full acceptance of AI.

In relation to Compatibility with Existing Systems, the ease of use is evaluated positively. 64.2% agree that AI is easy to use (AP=3.79 SD=.076), which indicates that it is not considered particularly difficult to use. However, compatibility with existing systems is more uncertain. Only 41.7% agree, while 36.7% maintain a neutral stance (AP=3.23, SD=.088). This shows concern about the practical integration of technology.

As for the complexity of AI, the trend is rather negative. A significant percentage (42.5%) disagree that AI is complex, while 29.2% agree, with the average value being below the neutral point (AP=2.79 SD=.094). This shows that, despite the caveats, the technology is not considered particularly difficult.

Overall, technological factors are evaluated positively, with an average value above neutral (AP=3.56 SD=.042). Participants seem to recognize the potential of AI, mainly in terms of performance and quality. At the same time, however, they express reservations about security and compatibility issues, which shows that the adoption of the technology is still in the process of adaptation and maturation.

Table 2. *Percentage distribution, A.P., S.D., Technological Factors*

	Strongly disagree	Disagree	Neither agree nor	Agree	Strongly agree	Average Price (A.P.)	Standard Deviation (S.D.)
<i>Scope and Potential of AI</i>							
1. AI can increase my work performance.	.8	.8	15.8	51.7	30.8	4.11	.069
2. AI can reduce errors in my work.	2.5	6.7	28.3	47.5	15.0	3.66	.082
3. AI can improve the quality of services we offer.	.8	7.5	23.3	49.2	19.2	3.78	.080
4. AI can automate many of my daily tasks.	3.3	9.2	21.7	41.7	24.2	3.74	.094
<i>Data Security and Privacy</i>							
5. I worry about data security when using AI.	5.0	21.7	23.3	32.5	17.5	3.36	.105
<i>Compatibility with Existing Systems</i>							
6. AI is easy to use.	.8	3.3	31.7	44.2	20.0	3.79	.076

7. AI is compatible with our existing systems.	4.2	17.5	36.7	34.2	7.5	3.23	.088
8. I am concerned about the complexity of AI.	10.0	32.5	28.3	26.7	2.5	2.79	.094
Technological Factors						3.56	.042

4.3.2. Organizational Factors

Regarding the perceptions of the participants on the organizational factors related to the adoption of AI (Table 4), and in particular regarding the Organizational Culture and Strategy, a rather positive picture emerges. The view that the adoption of AI is part of the company's strategy gathers very high approval rates (78.3%), with a high average value (AP=4.04 SD=.086). the attitude towards encouraging continuous learning and skills development is also positive (71.6% agreement, AP=3.96, SD=.082).

However, having a clear policy on the use of AI paints a more restrained picture. Only 50.8% agree, while a significant percentage maintains a neutral stance (30.8%), which is reflected in a lower average value (AP=3.45 SD=.099). This shows that, while the strategic direction looks positive, it is not always clear at the level of implementation.

When it comes to Management Support and Leadership, perceptions are generally positive, but not without reservations. Management's support for the use of AI is highly agreed (73.3%, AP=3.97 SD=.081), which indicates a positive attitude from leadership. However, when considering the provision of resources and time, the picture is different. Only 36.7% agree, while the largest percentage moves between neutrality and disagreement (59.2%), with a lower average value (AP=3.18, SD=.092).

The picture is similar in terms of clear guidance from the management. 45.9% agree, but a large percentage remains neutral (34.2%), which indicates a lack of clear direction (AP=3.37 SD=.094). In addition, regarding whether management takes into account employees' views on AI, almost half of the participants take a neutral stance (48.3%), while 42.5% agree (AP=3.46 SD=.078). This indicates limited inclusivity in decision-making.

In the Training and Skill Development **sub-section**, the results are more moderate. Only 43.4% consider that adequate training in AI is provided, while 25.8% disagree and 30.8% remain neutral (AP=3.21 SD=.102). The picture is even weaker in terms of participation in training programs, where only 45.8% say they have participated, while

40.8% disagree (AP=3.10 SD=.123). This shows a significant deficit in practical skills enhancement.

Overall, organizational factors are rated at moderate to positive levels (AP=3.53 SD=.065). Participants recognize that there is strategic direction and general support from management. However, clear gaps are found in the app. Lack of resources, limited guidance, and inadequate education are key obstacles. Organisms are in an adjustment phase. There is an intention to adopt AI, but there are not always the right structures in place to support it effectively.

Table 3. *Percentage distribution, A.P., S.D., Organizational Factors*

	Strongly disagree	Disagree	Neither agree nor	Agree	Strongly agree	A.P.	S.D.
<i>Organizational Culture and Strategy</i>							
9. AI adoption is part of our company's strategy.	1.7	5.8	14.2	43.3	35.0	4.04	.086
10. The company encourages continuous learning and skill development in AI.	.8	5.0	22.5	40.8	30.8	3.96	.082
11. Our company has a clear policy for using AI.	5.0	13.3	30.8	33.3	17.5	3.45	.099
<i>Management Support and Leadership</i>							
12. Company management supports the use of AI.	.8	5.0	20.8	43.3	30.0	3.97	.081
13. Management provides the necessary resources and time during working hours to adopt AI.	4.2	20.0	39.2	26.7	10.0	3.18	.092
14. There is clear guidance from management on adopting AI.	3.3	16.7	34.2	31.7	14.2	3.37	.094
15. I feel management values employees' opinions about AI.	.8	8.3	48.3	29.2	13.3	3.46	.078
<i>Training and Skill Development</i>							
16. The company provides sufficient AI training.	8.3	17.5	30.8	31.7	11.7	3.21	.102
17. I have participated in	13.3	27.5	13.3	27.5	18.3	3.10	.123

AI training programs.		
Organizational Factors	3.53	.065

4.3.3. Environmental Factors

Regarding the environmental factors influencing the adoption of AI (Table 5), a complex picture emerges with variations by dimension. Initially, the institutional and regulatory framework does not seem to function as a clear supporting factor. Only about 30% express a positive attitude, while almost half of the participants remain neutral (44.2%). The mean value (AP=3.00, SD=.084) reinforces this picture of uncertainty. In contrast, data protection regulations are recognized as a more substantial influencer, with almost half agreeing (49.1%) and several taking a neutral stance (38.3%) (AP=3.48 SD=.085). This shows that the regulatory framework restricts or directs rather than encourages adoption.

On an economic level, a relatively positive picture is formed, with some reservations. The majority consider that the financial situation of companies allows for investments in AI (58.3% agree), however a significant percentage remains cautious or neutral (30.8%) (AP=3.61 SD=.090). This finding shows that, although resources exist, they are not taken for granted or sufficient in all cases.

At the same time, external factors related to the business environment seem to exert intense pressure. A large percentage of participants recognize that competition acts as a key driver of adoption (71.7%, AP=3.83 SD=.077), while there is correspondingly high agreement on the need to maintain a competitive advantage through AI (70%, AP=3.87 SD=.080). These figures show that the adoption of technology is not only an option, but in many cases a necessity.

At the same time, the social dimension appears milder. About half of the participants consider that social acceptance affects the use of AI (48.3%), while a large percentage remains neutral (38.3%) (AP=3.45, SD=.077). This suggests that social pressure is not yet as intense.

Similarly, customer expectations do not seem to be a strong pressure factor. Just 30% agree that customers expect AI use, while the majority move between neutrality (43.3%) and disagreement (26.7%) (AP=3.03 SD=.092). This finding shows that customer demand has not yet matured. The role of technological development is particularly important. 68.3% agree that technological advancements are mandating the adoption of AI

(AP=3.81 SD=.086), indicating that advancements in technology are acting as a key driver of change.

Overall, environmental factors form a moderate to positive picture (AP=3.51 SD=.052). The adoption of AI appears to be influenced more by external pressures, such as competition and technological advancement, rather than institutional support or demand from customers. This suggests that the transition towards AI is not fully mature and requires amplification at both the policy and market levels.

Table 4. *Percentage distribution, A.P., S.D., Environmental Factors*

	Strongly disagree	Disagree	Neither agree nor	Agree	Strongly agree	A.P.	S.D.
<i>Legal and Regulatory Framework</i>							
18. The legal and regulatory framework supports AI adoption.	6.7	19.2	44.2	27.5	2.5	3.00	.084
19. Data protection regulations affect AI adoption.	2.5	10.0	38.3	35.8	13.3	3.48	.085
<i>Economic Factors</i>							
20. The company's financial situation supports investment in AI.	4.2	6.7	30.8	40.8	17.5	3.61	.090
<i>Market Trends and Competition</i>							
21. Market competition drives AI adoption.	.8	6.7	20.8	52.5	19.2	3.83	.077
22. AI is necessary to maintain our competitive advantage.	.8	5.8	23.3	45.8	24.2	3.87	.080
23. Social acceptance of AI affects its use in our company.	-	13.3	38.3	38.3	10.0	3.45	.077
24. Our customers expect us to use AI to improve services.	7.5	19.2	43.3	22.5	7.5	3.03	.092
25. Technological developments mandate AI adoption.	2.5	5.8	23.3	45.0	23.3	3.81	.086
Environmental Factors						3.51	.052

4.3.4. Human Factors

Regarding the respondents' perceptions of the human factors that influence the adoption of AI (Table 6), a multidimensional picture is formed that combines a positive attitude with reservations. Initially, in terms of attitudes and perceptions towards AI, a generally positive predisposition is recorded. The majority say they have a positive view (69.1% agree, $AP=3.90$ $SD=.078$), while the willingness to learn is even higher, with 88.3% stating that they wish to learn more ($AP=4.26$ $SD=.074$). At the same time, there is also strong enthusiasm for the potential of AI (72.5% agreement, $AP=3.98$ $SD=.088$). However, when weighing the benefits and risks is considered, the picture becomes more subdued. Only 47.5% consider that the benefits outweigh, while a significant percentage remains neutral (34.2%) ($AP=3.40$ $SD=.090$). This shows that, despite the positive attitude, there are still reservations.

In terms of knowledge and experience, the results are weaker. Only 33.3% consider that they have sufficient knowledge and experience, while the majority moves between neutrality (39.2%) and disagreement (27.5%) ($AP=3.06$, $SD=.082$). Similarly, participation in educational programs is limited, with 40.8% stating that they have not participated ($AP=2.99$ $SD=.109$). This finding highlights a significant gap in training.

In terms of adapting to change, respondents seem to recognize the need for further education. 80% agree that more training is needed to take full advantage of AI ($AP=4.04$, $SD=.085$). At the same time, most say they are relatively comfortable with the changes brought by AI (60.8% agreement, $AP=3.69$ $SD=.094$), which shows a positive willingness to adapt. However, there is no shortage of concerns. 53.3% believe that AI can replace some jobs ($AP=3.48$ $SD=.100$), while an even higher percentage of those who associate its use with possible job losses (61.7%, $AP=3.58$ $SD=.101$). These data show that acceptance coexists with fears of repercussions.

Of particular interest is the trust in AI. Respondents appear cautious, as only 24.2% say they trust the results of AI, while almost half remain neutral (47.5%) ($AP=2.98$ $SD=.078$). Similarly, AI's contribution to better decision-making is rated moderate (40% agreement, $AP=3.19$ $SD=.092$). This indicates limited confidence in the functional utilization of the technology.

At the level of personal and professional development, the perceptions are more positive. 58.4% believe that AI contributes to professional development ($AP=3.55$

SD=.093), while even more recognize the improvement of work experience (65.9%, AP=3.70 SD=.084). This reveals that AI is associated with growth opportunities.

Overall, human factors are in moderate to positive levels (AP=3.56 SD=.053). Participants appear positive and eager to learn, but at the same time indicate lack of knowledge and limited confidence. At the same time, concerns about work remain strong. This shows that the successful adoption of AI largely depends on education, fostering trust, and managing fears associated with change.

Table 5. *Percentage distribution, A.P., S.D., Human Factors*

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	A.P.	S.D.
<i>Employee Perceptions and Attitudes Toward AI</i>							
26. I have a positive opinion about AI.	.8	3.3	26.7	43.3	25.8	3.90	.078
27. I am willing to learn more about AI.	1.7	1.7	8.3	45.8	42.5	4.26	.074
28. I am excited about AI's capabilities.	.8	7.5	19.2	37.5	35.0	3.98	.088
29. In my opinion, the benefits of AI adoption outweigh the potential risks or downsides.	2.5	15.8	34.2	34.2	13.3	3.40	.090
<i>Experience and Knowledge in AI</i>							
30. I have sufficient knowledge and experience in AI.	3.3	24.2	39.2	30.0	3.3	3.06	.082
31. I have participated in AI training programs (also organizational but relevant to human knowledge).	10.0	30.8	20.0	28.3	10.8	2.99	.109
<i>Response to Change</i>							
32. I believe I need more training to fully leverage AI in my job.	2.5	4.2	13.3	46.7	33.3	4.04	.085
33. I feel comfortable with the changes AI brings to my work.	3.3	8.3	27.5	37.5	23.3	3.69	.094
34. I feel AI might replace some of my tasks.	5.0	13.3	28.3	35.0	18.3	3.48	.100

35. I feel AI use may lead to job losses.	6.7	9.2	22.5	42.5	19.2	3.58	.101
<i>Trust in AI and Its Results</i>							
36. I trust the outcomes produced by AI.	2.5	25.8	47.5	20.0	4.2	2.98	.078
37. I believe AI can help in making better decisions.	5.0	19.2	35.8	31.7	8.3	3.19	.092
<i>Personal and Professional Development through AI</i>							
38. I believe AI can contribute to my professional development.	2.5	15.0	24.2	41.7	16.7	3.55	.093
39. I believe AI can improve my work experience.	2.5	7.5	24.2	49.2	16.7	3.70	.084
Human Factors						3.56	.053

4.3.5. Intention to Adopt AI

Regarding the intention of the respondents to adopt AI, a particularly positive and dynamic picture is formed, which shows a strong willingness to use the technology in the near future (Table 7). Initially, there is a high intention to use AI tools immediately, with 74.1% stating that they intend to launch soon (AP=3.93 SD=.075). Similarly, an even higher percentage states that they plan to use AI on a regular basis in the near future (75.9%, AP=3.98 SD=.074). These figures show that AI is not seen as something distant, but as an immediate priority.

At the same time, there is a strong willingness to adopt new technologies. 78.3% say they are willing to leverage new AI tools when they become available (AP=4.01 SD=.074), while a corresponding percentage (80.9%) expect it to increase the use of AI over time (AP=4.01 SD=.070). This shows a clear tendency to enhance usage rather than simply maintain current practices.

The intention to use is also particularly high, provided that the company provides appropriate tools. 80.8% say they would actively use them if they were available (AP=4.06, SD=.070). This finding highlights the crucial role of organizational support in the eventual adoption.

On a more personal level, AI seems to be gradually integrating into everyday work. 73.3% say they see themselves using AI in their daily lives (AP=3.88 SD=.085), while 75% say they are likely to adopt it because they recognize its benefits (AP=3.96 SD=.080).

These results show that intention is not only theoretical, but is associated with specific expectations of utility.

Overall, the intention to adopt AI appears particularly high ($AP=3.98$ $SD=.066$), which is one of the most powerful findings of the survey. Participants seem to be ready to incorporate technology into their work, recognizing its benefits and showing a willingness to adapt. But, it's worth noting that high intent doesn't necessarily imply immediate or effective adoption. As shown by other dimensions of the survey, there are still limitations in terms of knowledge, education and organisational support. Therefore, intent acts as a positive indication of dynamics, but the actual use of AI will depend on whether existing gaps are filled.

Table 6. *Percentage distribution, A.P., S.D., Intention to Adopt AI*

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	A.P.	S.D.
40. I intend to start using AI tools in my work soon.	1.7	1.7	22.5	50.8	23.3	3.93	.075
41. I plan to use AI regularly in the near future.	.8	2.5	20.8	49.2	26.7	3.98	.074
42. I am willing to adopt new AI technologies when they become available.	.8	3.3	17.5	50.8	27.5	4.01	.074
43. I expect to increase my use of AI tools over time.	.8	2.5	15.8	56.7	24.2	4.01	.070
44. If the company provides AI tools, I will actively use them.	.8	1.7	16.7	52.5	28.3	4.06	.070
45. Using AI is something I see myself doing in my daily work.	1.7	7.5	17.5	47.5	25.8	3.88	.085
46. I am likely to adopt AI because I believe it will benefit my work.	1.7	3.3	20.0	47.5	27.5	3.96	.080
Intention to Adopt AI						3.98	.066

4.4 Reliability and Validity

Regarding the assessment of the reliability of the scales used in the survey, the results show overall satisfactory levels of internal consistency, with some variations between the factors (Table 1).

To begin with, organizational factors ($\alpha=0.867$, $\omega=0.864$), human factors ($\alpha=0.857$, $\omega=0.856$), and AI adoption intent ($\alpha=0.951$, $\omega=0.951$) show high reliability. These results show that the individual statements that make up each scale are consistent and accurately measure the same concept. In particular, the scale of adoption intention is extremely coherent.

The environmental factors also show satisfactory reliability ($\alpha=0.770$, $\omega=0.768$), which indicates that the scale is sufficiently stable and suitable for analysis, although not at the same high level as the previous ones.

In contrast, technological factors exhibit a low Cronbach's alpha value ($\alpha=0.522$), which indicates limited internal consistency. However, the McDonald's omega value ($\omega=0.662$) is higher and more acceptable, which indicates that the reliability of the scale is not as low as it initially seems. This finding is probably related to the diversity of the individual dimensions (e.g. utility, safety, compatibility), which are part of the same factor.

Overall, the set of variables shows high reliability ($\alpha=0.935$, $\omega=0.969$), which confirms that the research tool is robust and suitable for further statistical analysis. The results show that, while most scales are highly reliable, the dimension of technological factors needs to be carefully addressed, as it may involve heterogeneous elements.

Table 1. *Cronbach's Alpha Control- McDonald's Omega*

Factors and Adoption of AI Use	Number of declarations	Cronbach's Alpha	McDonald's Omega
Technological Factors	8	.522	.662
Organizational Factors	9	.867	.864
Environmental Factors	8	.770	.768
Human Factors	14	.857	.856
Intention to Adopt AI	7	.951	.951

Total	46	.935	.969
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4.5. RQ2: correlations between technological, organizational, environmental, and human factors and AI adoption intention

Regarding the correlations made between technological, organizational, environmental, and human factors and AI adoption intention, the results show statistically significant relationships and positive correlations between all factors and AI adoption intention (Table 8).

Initially, technological factors show a moderately positive correlation with adoption intention ($r=.480$, $p<.001$). This means that the more positively participants perceive the capabilities and functionality of AI, the more their intention to use it increases. However, the relationship is not particularly strong, which shows that they are not the dominant factor.

Organizational factors show a lower but also statistically significant correlation ($r=.366$, $p<.001$). This suggests that support from the organization and strategic direction influence intent, but to a lesser extent than other factors.

In contrast, environmental factors show a stronger relationship with adoption intention ($r=.571$, $p<.001$). This finding shows that external factors, such as competition and technological advancements, act as important catalysts.

Particularly strong is the relationship between human factors and adoption intention ($r=.846$, $p<.001$), which is the largest correlation. This shows that attitudes, perceptions, trust and willingness to learn play a crucial role. Simply put, adoption intention is more influenced by how participants think and feel.

At the same time, significant correlations are observed between the independent variables themselves. For example, environmental factors are strongly related to organizational ($r=.631$, $p<.001$) and human ($r=.595$, $p<.001$), while technological factors are more closely related to human ($r=.532$, $p<.001$). This shows that the factors do not work independently, but affect each other.

Overall, the results confirm that all factors are positively and statistically significantly related to AI adoption intention. However, the intensity of the relationship differs significantly. Human factors emerge as the most powerful, while organizational factors have the least effect in terms of correlation. It is worth noting that correlation

analysis demonstrates the existence of statistically significant relationships between variables, but does not substantiate a cause-and-effect relationship. Therefore, the findings are interpreted as evidence of association rather than evidence of a causal effect, which will be further examined through regression analysis (Cohen et al., 2003; Field, 2018).

Table 7. *Checking the correlation of factors for AI adoption*

		(1)	(2)	(3)	(4)	(5)
Technological Factors (1)	Pearson Correlation	1				
	Sig. (2-tailed)					
	N	120				
Organizational Factors (2)	Pearson Correlation	.269**	1			
	Sig. (2-tailed)	.003				
	N	120	120			
Environmental Factors (3)	Pearson Correlation	.416**	.631**	1		
	Sig. (2-tailed)	<.001	<.001			
	N	120	120	120		
Human Factors (4)	Pearson Correlation	.532**	.409**	.595**	1	
	Sig. (2-tailed)	<.001	<.001	<.001		
	N	120	120	120	120	
Intention to Adopt AI (5)	Pearson Correlation	.480**	.366**	.571**	.846**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	
	N	120	120	120	120	120

** . Correlation is significant at the 0.01 level (2-tailed).

4.6. RQ3: To what extent do technological factors influence the AI adoption, directly and/or indirectly through human factors?/ RQ4: How do organizational factors influence AI adoption, and to what extent is their influence mediated by human factors?/ RQ5: How do environmental factors influence AI adoption, what is the indirect role of human factors?/ RQ6: What is the direct role of human factors in shaping AI adoption intention?

Multiple linear regression was performed with the Enter method, where the dependent variable was defined as the intention to adopt AI and the technological, organizational, environmental and human factors as independent (Table 9). The Enter method was chosen because the independent variables had been determined theoretically and corresponded to

specific research hypotheses. all factors are introduced into the model at the same time to estimate the net contribution of each to the AI adoption intention, while controlling for the effect of the remaining variables (Meyers et al., 2013; Tabachnick & Fidell, 2013).

Table 8. *Variables Entered/Removed^a*

Variables Entered	Variables Removed	Method
Technological Factors, Organizational Factors, Environmental Factors, Human Factors	.	Enter

a. Dependent Variable: Intention to Adopt AI

b. All requested variables entered.

Initially, in terms of model appropriateness, a very high correlation coefficient ($R=.851$) is obtained, which shows a strong overall relationship between the independent variables and adoption intention (Table 10). The value of R^2 is particularly high ($R^2=.723$), while the adjusted R^2 (Adjusted $R^2=.714$) remains at similar levels. This means that about 72% of the variation in adoption intent is explained by the model. This is a very powerful result, which indicates high interpretive ability. At the same time, the Durbin-Watson value (2,249) indicates that there is no problem of self-correlation of the residues.

Table 9. *Model Summary^b*

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	PRESS	Durbin-Watson
1	.851a	.723	.714	.389	19.474	2.249

a. Predictors: (Constant), Technological Factors, Organizational Factors, Environmental Factors, Human Factors

b. Dependent Variable: Intention to Adopt AI

Variance analysis (ANOVA) confirms that the model is statistically significant overall ($F=75.206$, $p<.001$). This means that, as a whole, independent variables contribute significantly to predicting adoption intent.

Table 10. ANOVAa

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	45.582	4	11.395	75.206	<.001b
	Residual	17.425	115	.152		
	Total	63.007	119			

a. Dependent Variable: Intention to Adopt AI

b. Predictors: (Constant), Technological Factors, Organizational Factors, Environmental Factors, Human Factors

However, when the individual factors are examined, the picture varies significantly (Table 12). Technological factors have a very low and non-statistically significant effect ($\beta=.028$, $p=.637$). Similarly, organizational factors do not have a significant effect and even have a negative coefficient ($\beta=-.034$, $p=.595$), which indicates that they do not substantially affect adoption intent. Environmental factors show a positive but marginally non-statistically significant effect ($\beta=.122$, $p=.096$). This result shows a tendency to influence, but it is not enough to support it with certainty.

In contrast, human factors (Employee Perceptions and Attitudes Toward AI, Experience and Knowledge in AI, Response to Change, Trust in AI and Its Results, Personal and Professional Development through AI), emerge as the determining factor. They have a very high and statistically significant effect ($\beta=.772$, $p<.001$). The intensity of the coefficient indicates that they are the key predictor of AI adoption intent. Simply put, the attitude, trust, knowledge and willingness of the participants are what mainly determine whether they will adopt the technology.

The equation of the regression model is: $Y=b_0+b_1x_1$. Therefore, for the acceptance of the adoption of AI $=-.049+.968*$ Human factors. In terms of their impact on the construction of the predictability model: If human factors (Employee Perceptions and Attitudes Toward AI, Experience and Knowledge in AI, Response to Change, Trust in AI and Its Results, Personal and Professional Development through AI) increase by one point and the remaining variables remain constant, then the acceptance of AI use will increase by .968 times.

Table 11. Coefficients^a

Model		Unstandardized		Standardized		Collinearity	
		Coefficients		Coefficients		Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance VIF
1	(Constant)	-.049	.308		-.160	.873	
	Technological Factors	.044	.094	.028	.473	.637	.702 1.425
	Organizational Factors	-.034	.064	-.034	-.533	.595	.599 1.668
	Environmental Factors	.155	.092	.122	1.678	.096	.457 2.187
	Human Factors	.968	.083	.772	11.642	<.001	.547 1.829

a. Dependent Variable: Intention to Adopt AI

In terms of multilinearity, VIF values range at acceptable levels (1,425–2,187), which indicates that there is no serious correlation problem between the independent variables. Graph (2) of the residues shows that the values are distributed approximately normally, in a symmetric form around zero. This observation suggests that the assumption of residue regularity, which is a basic condition for the application of linear regression, is satisfied. Also, the Normal P-P Plot graph (3) shows that the points are close to the diagonal line. This suggests that the residues follow a roughly normal distribution, confirming the validity of the model.

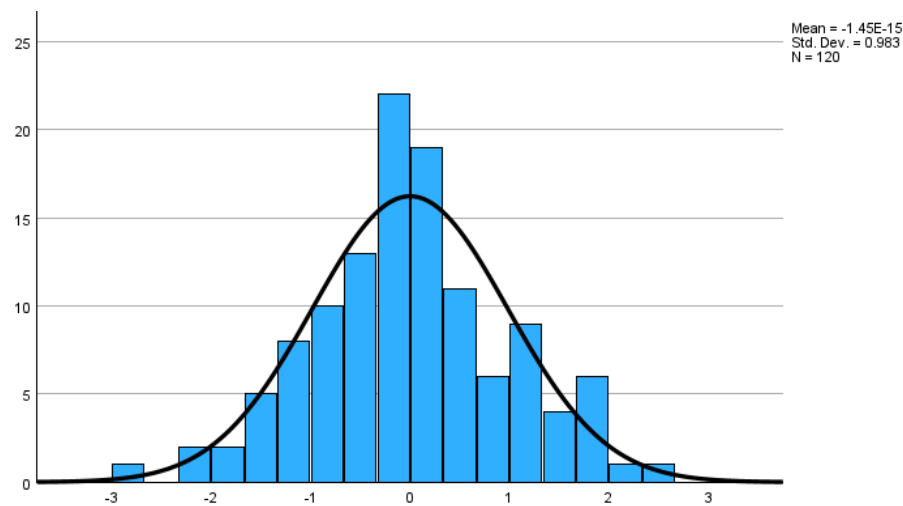


Figure 2. *Regularity of residues*

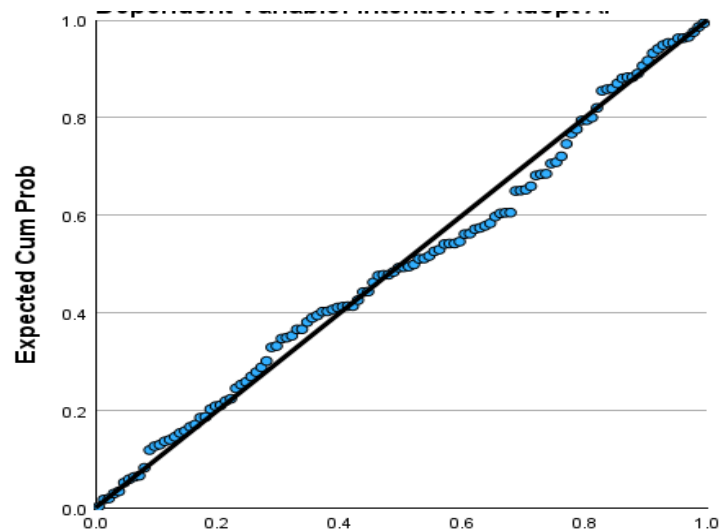


Figure 3. *Normal P-P Plot*

Overall, the results show a particularly interesting pattern. Although all factors appear positively correlated with adoption intention at the correlation level, when examined simultaneously through regression, only human factors retain their importance. This suggests that the rest of the factors indirectly affect or overlap with the human ones.

These findings show that while the organizational and technological environment is important, it is not enough on its own to drive the adoption of AI. The determining factor seems to be the human factor, i.e. how the users perceive, understand and accept the technology themselves.

In addition, the loss of significance of the remaining factors in regression may be related to overlaps between the variables, as had already been shown by the correlation analysis.

This reinforces the need for further investigation, potentially with more complex models. Overall, the results highlight that the successful adoption of AI depends primarily on the human factor and less on technological or organizational conditions.

4.10. RQ7: Do human factors mediate the relationship between technological, organizational, and environmental factors and AI adoption?

In the context of investigating the indirect effect of technological factors on AI adoption intention, a mediation analysis was performed using PROCESS Model 4. Based on the regression results, only Human Factors had a strong and statistically significant effect on AI adoption intention, while the remaining factors were not significant. This creates a very strong hypothesis, that the other factors indirectly influence the intention, through human factors.

a) Technological factors were defined as an independent variable, human factors as a mediator and the intention to adopt AI as a dependent variable (Annex 2, Table 13). First, the effect of technological factors on human factors was examined. The results show that the effect is positive and statistically significant ($\beta=.6777$, $p<.001$). The model is also statistically significant overall ($F=46.52$, $p<.001$), explaining about 28.3% of the variation in human factors ($R^2=.2828$). This finding shows that the more positively the participants perceive the technology, the more positive their attitudes and perceptions towards AI are.

Next, the influence of both technological and human factors on adoption intention was examined. The overall model appears particularly strong ($R^2=.7163$, $F=147.67$, $p<.001$), explaining over 71% of the variation in intent. However, only human factors show a statistically significant effect ($\beta=1.0319$, $p<.001$), while technological factors are not significant ($\beta=.0673$, $p=.4702$).

The direct influence of technological factors on adoption intention is nonstatistically significant ($p=.4702$), which confirms that there is no direct relationship when the mediator is considered. In contrast, the indirect effect through human factors is positive and statistically significant (effect=.6993), as the confidence interval (BootLLCI=.4656, BootULCI=.9447) does not include zero. This result is a clear indication of the existence of mediation.

b) Organizational factors were defined as an independent variable, human factors as a mediator and the intention to adopt AI as a dependent variable (Annex 2, Table 14). First,

the effect of organizational factors on human factors was examined. The results show that the effect is positive and statistically significant ($\beta=.3312$, $p<.001$). The model is statistically significant ($F=23.69$, $p<.001$) and explains 16.7% of the variation in human factors ($R^2=.1672$). This finding suggests that a supportive organizational environment contributes to the formation of positive attitudes and perceptions towards AI.

Subsequently, the influence of organizational and human factors on adoption intention was examined. The model appears particularly strong ($R^2=.7155$, $F=147.12$, $p<.001$), explaining over 71% of the variance. However, only human factors show a statistically significant effect ($\beta=1.0473$, $p<.001$), while organizational factors are not statistically significant ($\beta=.0251$, $p=.6483$).

The direct influence of organizational factors on adoption intent is nonstatistically significant ($p=.6483$), indicating that they do not directly affect intent when the mediator is considered.

In contrast, the indirect effect through human factors is positive and statistically significant (effect=.3469), since the confidence interval (BootLLCI=.1983, BootULCI=.5084) does not include zero. This finding confirms the existence of mediation.

c) Environmental factors were defined as an independent variable, human factors as a mediator and the intention to adopt AI as a dependent variable (Annex 2, Table 15). At the beginning, the effect of environmental factors on human factors was examined. The results show that the effect is positive and statistically significant ($\beta=.6043$, $p<.001$). The model is also statistically significant ($F=64.66$, $p<.001$), explaining 35.4% of the variation in human factors ($R^2=.3540$). This finding suggests that external factors, such as competition, technological advancements, and the institutional framework, substantially influence participants' attitudes and perceptions towards AI.

Subsequently, the influence of environmental and human factors on adoption intention was examined. The overall model is particularly strong ($R^2=.7222$, $F=152.09$, $p<.001$), explaining over 72% of the variation in intent. However, only human factors show a statistically significant effect ($\beta=.9811$, $p<.001$), while environmental factors are not statistically significant ($\beta=.1346$, $p=.0838$), although they show a marginal trend of effect.

The direct influence of environmental factors on adoption intent is nonstatistically significant ($p=.0838$), indicating that they do not directly affect intent when the mediator is considered. In contrast, the indirect effect through human factors is positive and

statistically significant (effect=.5929), since the confidence interval (BootLLCI=.4070, BootULCI=.8026) does not include zero. This finding confirms the existence of mediation.

The results confirm the same pattern observed in the previous analyses. Environmental factors do not directly influence the intention to adopt AI, but their effect is carried out indirectly through human factors. However, in contrast to technological and organizational factors, there is a marginal direct effect ($p \approx .084$), which indicates that environmental factors may have a small direct influence, which is not statistically sufficient in this sample.

The existence of a significant indirect effect in combination with a non-significant direct effect also indicates full mediation. That is, external conditions affect intent only through their effect on user attitudes, trust, and readiness. On a theoretical level, this finding is particularly important, as it shows that even strong external factors, such as competition or technological advances, are not enough to directly lead to the adoption of AI. Their effect depends on how they are perceived by the users themselves.

4.11. RQ8: Do technological, organizational, or environmental factors moderate the relationship between human factors and AI Adoption?

This section is linked to the research question that examines whether technological, organizational and environmental factors modify the relationship between human factors and the intention to adopt AI. Specifically, it was investigated whether the influence of human factors on the intention to use AI varies depending on the level of technological readiness, organizational support or environmental pressures perceived by employees.

To investigate the modifying effect, moderation analysis was performed using PROCESS (Model 1).

(a) The interaction between human and technological factors in terms of the intention to adopt AI was examined (Annex 2, Table 16). The dependent variable was defined as the intention to adopt AI, the independent variable was human factors and the modifying variable was technological factors. In addition, the term interaction between human and technological factors (Human $\times$ Technological) was included, to examine whether the relationship between the variables is different. The overall model is statistically significant

($F=97.70$, $p<.001$) and exhibits very high interpretive ability ($R^2=.7164$), explaining about 71.6% of the variation in adoption intent.

In terms of the main effects, human factors have a positive and statistically significant effect on adoption intention ($\beta=1.1335$, $p=.0031$), once again confirming their decisive role. In contrast, technological factors do not have a statistically significant effect ($\beta=.1679$, $p=.6565$).

The crucial element of the analysis is the interaction term (Human $\times$ Technological). The results show that this term is not statistically significant ($\beta=-0.0291$, $p=.7833$). In addition, the change in R^2 due to the interaction is practically zero ($\Delta R^2=.0002$, $p=.7833$), which confirms that adding the interaction does not improve the model.

The bootstrap results reinforce the same conclusion, as the confidence interval for the interaction condition (BootLLCI=-0.2175, BootULCI=0.2409) includes zero, indicating the absence of a statistically significant modifying effect.

The findings show that technological factors do not modify the relationship between human factors and the intention to adopt AI. In other words, the influence of human factors remains constant regardless of the level of technological factors. This result is particularly important, as it suggests that the importance of human factors is universal and does not depend on the technological environment. Even in environments with high technological readiness, adoption intent is primarily determined by attitudes, perceptions, and levels of trust. This finding reinforces the results of regression and mediation analysis, where human factors emerged as the main influencing mechanism. In addition, it shows that technological factors do not strengthen or weaken this relationship, but operate independently.

(b) The interaction between human and organizational factors in terms of AI adoption intention was examined (Annex 2, Table 17). The overall model is statistically significant ($F=98.71$, $p<.001$) and shows very high interpretive ability ($R^2=.7185$), explaining about 71.9% of the variation in adoption intent. In terms of the main effects, Human factors show a strong and statistically significant positive effect on adoption intention ($B=1.3661$, $p<.001$), confirming their stable and dominant contribution. In contrast, organizational factors do not have a statistically significant effect ($\beta=.3512$, $p=.2387$). The crucial element of the analysis is the term interaction (Human $\times$ Organizational). The results show that this term is not statistically significant ($\beta=-0.0906$, $p=.2654$). In addition, the increase

in the explained variance due to the interaction is very small ($\Delta R^2=.0030$) and non-statistically significant ($p=.2654$), suggesting that adding the interaction does not substantially improve the model. The bootstrap results confirm the same conclusion, as the confidence interval for the interaction condition (BootLLCI=-0.3772, BootULCI=0.1062) includes zero, indicating the absence of a statistically significant modifying effect.

Organizational factors do not modify the relationship between human factors and the intention to adopt AI. In other words, the influence of human factors remains strong and stable regardless of the level of organizational support or strategy. This finding is particularly important, as it shows that even in organizations with different levels of culture, leadership, or education, adoption intent is primarily determined by individual factors, such as attitudes, perceptions, and trust. In addition, the fact that the organizational factor is neither directly relevant nor acts as a moderator reinforces the view that its influence is indirect, as has already been demonstrated through mediation analysis. That is, the organism influences intention only through its effect on human factors.

(c) The interaction between human and environmental factors in terms of AI adoption intention was examined (Annex 2, Table 18). The overall model is statistically significant ($F=101.87$, $p<.001$) and exhibits a very high interpretive ability ($R^2=.7249$), explaining about 72.5% of the variation in adoption intent.

In terms of the main effects, human factors show a strong and statistically significant positive effect ($\beta=1.3224$, $p=.0001$), confirming their stable and dominant contribution. In contrast, environmental factors do not have a statistically significant effect ($\beta=.4917$, $p=.1573$).

The important element of the analysis is the interaction term (Human $\times$ Environmental). The results show that this term is not statistically significant ($\beta=-0.0993$, $p=.2911$). In addition, the increase in explained variance due to interaction is very small ($\Delta R^2=.0027$) and non-statistically significant ($p=.2911$), suggesting that adding interaction does not substantially improve the model.

The bootstrap results confirm the same conclusion, as the confidence interval for the interaction condition (BootLLCI=-0.2945, BootULCI=0.0939) includes zero, indicating the absence of a statistically significant modifying effect. Environmental factors do not modify the relationship between human factors and the intention to adopt AI. That is, the influence of human factors remains constant regardless of the level of external conditions, such as competition or technological advancements. This finding is important,

as it shows that even strong external pressures do not strengthen or weaken the relationship between attitudes and adoption intention. In other words, the decision to adopt AI appears to be primarily internal rather than context-dependent. Moreover, the fact that environmental factors function neither as direct predictors nor as moderators, but have had a significant indirect influence on mediation analysis, reinforces the overall interpretation that their influence is exerted indirectly through human factors. Therefore, technological, organizational, and environmental factors do not significantly alter the relationship between human factors and AI adoption intention. Therefore, the corresponding research question was not empirically confirmed in this sample, which suggests that human factors directly and relatively autonomously influence the intention to adopt AI.

4.12. RQ9: To what extent are employees' demographic and occupational characteristics associated with AI adoption intention?

This section is linked to the research question that examines whether the intention to adopt AI varies according to the demographic and occupational characteristics of employees. For this purpose, variables such as gender, age, educational level, work experience, digital skill level, previous experience of using AI and business size were considered.

Gender. Regarding the investigation of differences in the intention to adopt AI based on gender, the results show that men show a slightly higher average ($AP=4.05$, $SD=0.648$) compared to women ($AP=3.92$, $SD=0.782$). However, this difference is not statistically significant ($p=0.336$), which suggests that gender does not seem to substantially influence the intention to adopt AI. the effect magnitude is small (Cohen's $d=0.173$), confirming that the difference between the two groups is limited and practically negligible. Overall, it appears that men and women show a similar attitude towards the adoption of AI, without substantial differences (Annex 2, Table 19, 20, 21). .

Age. In terms of investigating differences in AI adoption intention based on age, the results of the variance analysis (ANOVA) show that there are no statistically significant differences between age groups ($F=1,052$, $p=0.384>0.05$). This finding suggests that age does not seem to have a meaningful influence on AI adoption intention. regardless of age category, they have a similar level of acceptance of AI (Annex 2, Table 22).

Years of service. As for the intention to adopt AI based on years of work experience, the results of the variance analysis (ANOVA) show that there are no statistically significant

differences between the groups ($F=0.511$, $p=0.676$). This finding reveals that working time does not seem to substantially affect the intention to adopt AI. Participants show similar levels of acceptance, regardless of their professional experience (Annex 2, Table 23).

Higher degree. Regarding the investigation of differences in the intention to adopt AI based on the higher degree, the results of the variance analysis (ANOVA) show that there are no statistically significant differences between the groups ($F=1,055$, $p=0,389$). The finding shows that the level of education does not seem to substantially affect the intention to adopt AI. Respondents have a similar attitude towards AI, regardless of their qualification (Annex 2, Table 24). .

Job position. In terms of the intention to adopt AI based on the job (Director/Deputy Director, Supervisor, Staff), the results of the variance analysis (ANOVA) show that there are no statistically significant differences between the groups ($F=.196$, $p=0.822$). The finding shows that the job does not seem to substantially affect the intention to adopt AI. Respondents have a similar attitude towards AI, regardless of their field of work (Annex 2, Table 25).

Number of employees. Regarding the investigation of differences in the intention to adopt AI based on the number of employees, the results show that the size of the company is a factor that differentiates the attitude of the participants to some extent. Initially, the variance analysis (ANOVA) showed that there are overall statistically significant differences between the groups ($F=3,475$, $p=0.018$). This means that the intention to adopt AI is not the same across all business categories (Table 26).

Table 26. ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Intention to Adopt AI	Between Groups	9.564	3	3.188	3.475	.018
	Within Groups	134.855	147	.917		
	Total	144.419	150			

To identify more specifically where these differences lie, a multi-comparison test (Tukey) was performed (Table 27). The results show that the only statistically significant difference is found between enterprises with 1–100 employees and enterprises with 401–

1000 employees (Mean Difference=-0.605, $p=0.018$). In all other comparisons, no statistically significant differences are observed. This means that smaller insurance companies with a number of employees (1-100) have a statistically lower acceptance of the use of AI by 0.605 times less than medium-sized insurance companies (401-1000).

Employees in medium-sized businesses have a different and probably more positive attitude towards the adoption of AI than those working in smaller companies. On the contrary, no differentiations between other categories arise, which indicates that the effect of size is not linear. This result may be linked to the fact that medium-sized enterprises often have a better balance between resources and flexibility. On the one hand, they have adequate infrastructure and investment possibilities, while on the other hand, they are not as bureaucratically complex as very large companies. In contrast, smaller businesses may be more cautious due to limited resources or lower technological readiness. Overall, the results show that, unlike other demographics that did not influence adoption intent, the size of the business is a factor that can differentiate attitudes towards AI, even in specific cases.

Table 27. Multiple Comparisons

Tukey HSD							
Dependent Variable	(i) Number of Employees	(j) Number of Employees	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intention to Adopt AI	1-100	101-400	-.067	.174	.980	-.52	.39
		401-1000	-.605*	.203	.018	-1.13	-.08
		1001 and above	.192	.197	.765	-.32	.71
	101-400	1-100	.125	.233	.950	-.48	.73
		401-1000	-.413	.255	.371	-1.08	.25
		1001 and above	.067	.174	.980	-.39	.52
	401-1000	1-100	-.125	.233	.950	-.73	.48
		101-400	-.538	.238	.112	-1.16	.08
		1001 and above	.605*	.203	.018	.08	1.13
	1001 and above	1-100	.413	.255	.371	-.25	1.08
		101-400	.538	.238	.112	-.08	1.16
		401-1000	-.067	.174	.980	-.52	.39

*. The mean difference is significant at the 0.05 level.

Experience using AI. Regarding the investigation of differences in the intention to adopt AI based on previous experience of using AI, the results show clear and statistically

significant differences between the participants. Initially, the descriptors show that those with experience in using AI show a higher average adoption intention ($M=4.13$, $SD=0.628$) compared to those without relevant experience ($M=3.74$, $SD=0.810$). This difference shows a more positive attitude towards AI on the part of already familiar users (Table 28).

Table 28. Group Statistics

	AI Usage Experience	N	Mean	Std. Deviation	Std. Error Mean
Intention to Adopt AI	Yes	73	4.13	.628	.073
	No	47	3.74	.810	.118

Statistical analysis (t-test) confirms that this difference is statistically significant ($t=2.987$, $p=0.003$), which means that the experience of using AI substantially influences adoption intent (Table 29). Familiarity with technology seems to enhance acceptance and willingness for further use.

Table 29. Independent Samples Test

		Levene's Test for Equality of Variances		Significance				
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference
Intention to Adopt AI	Equal variances assumed	1.068	.304	2.987	118	.002	.003	.394
	Equal variances not assumed			2.828	80.720	.003	.006	.394

In addition, the effect magnitude is moderate to high (Cohen's $d=0.559$), which indicates that the difference is not only statistically significant, but also practically significant (Table 30). Overall, the results highlight experience as one of the most essential differentiators. Unlike other demographics that did not show significant differences, the

previous use of AI appears to significantly enhance adoption intent, which underscores the importance of familiarity and hands-on experience in the process of accepting new technologies.

Table 30. Independent Samples Effect Sizes

		Standardizer a	Point Estimate	95% Confidence Interval	
				Lower	Upper
Intention to Adopt AI	Cohen's d	.705	.559	.184	.931
	Hedges' correction	.709	.555	.183	.925
	Glass's delta	.810	.486	.104	.863

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

ICT skill level. In terms of investigating differences in AI adoption intention based on ICT skill level, the results show that digital skill level is an important differentiator. Initially, the variation analysis (ANOVA) showed that there are overall statistically significant differences between groups ($F=3,647$, $p=0.015$). This means that AI adoption intent is not the same for all skill levels (Table 31).

Table 31. ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Intention to Adopt AI	Between Groups	5.431	3	1.810	3.647	.015
	Within Groups	57.576	116	.496		
	Total	63.007	119			

Based on the individual comparisons (Tukey), it appears that significant differences are mainly found between people with very low skills (Minimal) and those with higher skills (Table 32). Specifically, those with Good skills show a higher adoption intention (Mean Difference=-0.752, $p=0.011$) by 0.752 times compared to those with minimal skills

(Minimal). Correspondingly higher is the intention to use AI for those with excellent skills (Excellent) compared to the less familiar (Mean Difference = -0.803, $p=0.038$) by 0.803 more. On the contrary, there are no significant differences between the intermediate levels (Basic, Good, Excellent). This finding shows that the main point of differentiation is not so much the transition from one level to the next, but mainly the difference between very low and medium/high skills. In other words, when participants go beyond a basic level of digital proficiency, their attitude towards AI becomes more positive. Overall, the results highlight the importance of digital skills as a critical factor in AI adoption. Unlike other demographics that did not show any variations, here it appears that technological familiarity substantially influences adoption intention, highlighting the need to enhance digital skills in the insurance industry.

Table 32. Multiple Comparisons

Tukey HSD							
Dependent Variable	(I) ICT skill level	(J) ICT skill level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intention to Adopt AI	Minimal	Basic	-.565	.256	.127	-1.23	.10
		Good	-.752*	.239	.011	-1.37	-.13
		Excellent	-.803*	.296	.038	-1.58	-.03
	Basic	Minimal	.565	.256	.127	-.10	1.23
		Good	-.186	.153	.620	-.59	.21
		Excellent	-.238	.233	.737	-.84	.37
	Good	Minimal	.752*	.239	.011	.13	1.37
		Basic	.186	.153	.620	-.21	.59
		Excellent	-.052	.214	.995	-.61	.51
	Excellent	Minimal	.803*	.296	.038	.03	1.58
		Basic	.238	.233	.737	-.37	.84
		Good	.052	.214	.995	-.51	.61

*. The mean difference is significant at the 0.05 level.

This section is linked to the research question that examines whether the intention to adopt AI varies according to the demographic and occupational characteristics of employees. For this purpose, variables such as gender, age, educational level, work experience, digital skill level, previous experience of using AI and business size were considered.

4.13. Discussion

The purpose of this study was to investigate the factors influencing the adoption of AI in the insurance industry, with an emphasis on technological, organizational, environmental and human factors, as well as their direct and indirect role. At the same time, the research sought to examine the role of human factors as a mediation mechanism. The discussion that follows is based on the findings of a sample of 120 employees of insurance companies in Athens, Attica. Overall, the results show that the intention to adopt AI is high, but the path to its actual utilization is not linear. At the level of simple correlations, all key factors are positively related to adoption intent. But when examined at the same time, the human factor emerges as the only consistently strong direct predictive factor. It is also worth noting that, although the general purpose of the study is also related to organizational efficiency and quality of services, in the empirical part these dimensions were mainly reflected through employees' perceptions of improving performance and quality of services, and not through independent objective performance indicators. Specifically, with the research questions:

RQ1: What are the perceptions of insurance company employees regarding the technological, organizational, environmental, and human factors associated with AI adoption?

The findings show an overall moderate to positive picture. Technology factors were rated positively (Mean=3.56), with the strongest agreement that AI can increase work performance (Mean=4.11). Organisational factors also moved to moderate to positive levels (Mean=3.53), mainly in terms of strategic direction and administrative support. Environmental factors had a similar average (Mean=3.51), with competition and technological progress acting as the strongest external pressures. Finally, human factors also appeared moderate-to-positive (Media=3.56), with a very high willingness to learn (Media=4.26), but relatively lower confidence in AI outcomes (Media=2.98). This picture shows that employees do not view AI with rejection; instead, they recognize its potential, but maintain specific reservations. This is perfectly compatible with the theoretical framework of work. The TOE framework explains why employees positively evaluate utility, organizational strategy, and external pressures, while the TAM and UTAUT models

help to understand why the final attitude remains tied to the perceived one utility, ease of use, trust, and facilitating conditions (Gupta et al., 2022; Nguyen et al., 2024). At the same time, the literature on the insurance industry shows that AI can indeed improve efficiency, quality of service, pricing, claims management and fraud detection, but at the same time raises issues of transparency, data protection and accountability (Eling et al., 2022). The insurance industry is in a transitional stage. AI is no longer considered a distant technology, but neither is it a fully established practice. Its acceptance is real, but it is accompanied by a need for clearer organisational support, more training and greater trust.

RQ2: What are the correlations between technological, organizational, environmental, and human factors and the intention to adopt AI?

The correlations were all positive and statistically significant. The strongest relationship emerged between human factors and adoption intention ($r=.846$, $p<.001$). This was followed by environmental factors ($r=.571$, $p<.001$), technological factors ($r=.480$, $p<.001$) and, finally, organizational factors ($r=.366$, $p<.001$). This finding is particularly important because it shows that adoption intent does not result from a single factor. Instead, it is a product of the interaction of different levels of influence. However, the hierarchy of correlations shows that not all factors have the same specific weight. The human dimension is the one that is closest to the final intention. This is consistent with technology acceptance models, where attitudes, perceptions, trust, and personal readiness are the closest mechanism that drives from technology to its use (Nguyen et al., 2024). At the same time, it is also compatible with the international literature of the insurance industry, which shows that, even when technological capabilities are mature, adoption depends on whether employees consider AI to be useful, safe and compatible with their role (Gupta et al., 2022; Eling et al., 2022).

RQ3: To what extent do technological factors influence the adoption of AI, directly and/or indirectly through human factors?

At the level of multiple regression, technological factors did not have a statistically significant direct effect on adoption intent ($\beta=.028$, $p=.637$). In contrast, in the mediation analysis they were found to significantly influence human factors ($\beta=.6777$, $p<.001$),

while their indirect effect on adoption intention through human factors was significant (indirect effect=.6993, 95% CI [.4656, .9447]). The direct effect of technological factors, when the mediator is introduced, remains insignificant ($\beta=.0673$, $p=.4702$). It seems that technological characteristics alone are not enough to produce adoption intention. The employee does not adopt AI simply because they perceive it as useful, easy to use, or functionally advanced. Technological characteristics need to be transformed into a positive personal attitude, a sense of competence, confidence and readiness. This is exactly where TOE and TAM meet. TOE explains the importance of technological features, while TAM explains why utility and usability ultimately act through user perceptions (Gupta et al., 2022; Nguyen et al., 2024).

This includes the discussion of H1 (Technological factors (scope and potential of AI, data security and privacy, compatibility with existing systems) have a positive and statistically significant effect on the intention to adopt AI (in insurance companies).). If the first hypothesis is interpreted as a direct influence of technological factors on the adoption intention, then it is not confirmed. The result is interesting, because it differs from the study of Gupta et al. (2022), where technological factors were statistically significant direct predictors. Technology only becomes important when it goes through the way employees experience it. This explains why adoption intention is ultimately more of a psychosocial phenomenon than a strictly technical one.

RQ4: How do organizational factors influence AI adoption, and to what extent is their influence mediated by human factors?

Organizational factors did not have a statistically significant direct effect on the multifactorial model ($\beta=-.034$, $p=.595$). In the mediation analysis, however, they positively and significantly influenced human factors ($\beta=.3312$, $p<.001$), while their indirect effect on adoption intention through human factors was also significant (indirect effect = .3469, 95% CI [.1983, .5084]). When human factors were included in the model, The direct organizational effect remained insignificant ($B=.0251$, $P=.6483$). This result shows that organizational strategy, administrative support and training are important, but not in a direct way. It is not enough for a company to state that it has an AI strategy or that management is positive. These only become practical when they are translated into positive attitudes of employees, a sense of participation, trust and a willingness to

learn. This interpretation is fully linked to the theoretical part of the work, where organizational culture, leadership, and skill development are presented as conditions that facilitate the acceptance of innovation, not as automatic adoption mechanisms (Gupta et al., 2022). At the same time, it is consistent with the approach of facilitating conditions in the technology acceptance literature, as highlighted in Nguyen et al. (2024). At this point, H2 (Organizational factors (organizational culture and strategy, management support and leadership, training and development) have a positive and statistically significant effect on the intention to adopt AI (in insurance companies) is also discussed. The hypothesis of a positive and statistically significant direct effect of organizational factors is not confirmed. However, it does not mean that organizational factors are indifferent. On the contrary. It functions as the framework within which human attitudes are built or weakened. The organism does not drive adoption on its own, but can create the right or inappropriate psychological environment for it to happen.

RQ5: How do environmental factors influence AI adoption, and what is the indirect role of human factors?

Environmental factors showed a marginal but not statistically significant direct effect on adoption intent in the regression model ($\beta=.122$, $p=.096$). In the mediation analysis, their effect on human factors was positive and significant ($\beta=.6043$, $p<.001$), while the indirect effect through human factors was also significant (indirect effect=.5929, 95% CI [.4070, .8026]). The direct effect on the final model remained insignificant, although marginal ($\beta=.1346$, $p=.0838$). This result is of particular importance. It shows that competition, technological development, the institutional framework and market conditions create pressure for change, but they are not enough on their own to drive the intention to use. External pressure must first become an internal belief. The results of the survey also showed that environmental factors were evaluated more positively in terms of competition and technological progress, but much more restrained in terms of institutional support and customer expectations. This indicates a market that is moving towards AI but has not yet fully matured. This interpretation aligns with the theoretical framework of TOE, where the environment does not always function as a direct mechanism, but as a source of pressure, opportunities, and constraints that must be

interpreted by the organization and its people (Gupta et al., 2022). In the same vein, the study by Eling et al. (2022) shows that AI is changing the external ecosystem of insurance, It creates new markets, new risks and new compliance requirements, but its exploitation depends on whether the organization can turn them into sustainable internal adaptation. H3 (Environmental factors (regulatory framework, economic conditions, competition, customer expectations, technological developments) have a positive and statistically significant effect on the intention to adopt AI (in insurance companies), so it is not confirmed as a direct hypothesis. However, environmental factors are not negligible. Research shows that they are essential, but their action is mainly indirect and passes through the attitude of employees.

RQ6: What is the direct role of human factors in shaping AI adoption intention?

This question gave the clearest and most powerful result of the entire study. Human factors had a very strong and statistically significant direct effect on adoption intention ($b=.772$, $p<.001$), while their correlation with intention was also the strongest of all ($r=.846$, $p<.001$). The final model even showed that, If the human factors increase by one point, the adoption intent increases by .968 points, when the remaining factors remain constant. The adoption of AI in the insurance industry is mainly judged by how employees think and feel about it. When there is a positive attitude, a willingness to learn, a comfort with change, confidence in the results and a sense that AI can enhance professional growth, then the intention to adopt becomes stronger. Low knowledge, low confidence or fear of losing a job role, adoption slows down. This fits perfectly with the approach of TAM and UTAUT, but also with the findings of Nguyen et al. (2024), where attitudes towards adoption were the strongest predictor of intention. In the insurance industry, the success of AI is not a purely technical issue, but largely depends on the acceptance and intention of its use by employees who are called upon to integrate it into their daily processes (Dwivedi et al., 2021 ; Venkatesh et al., 2003). Factors such as perceived utility, ease of use, trust in AI systems, organizational support, and concerns about the job role significantly influence user acceptance of the technology (Davis, 1989; Glikson & Woolley, 2020). Especially in financial and insurance service organizations, the successful adoption of AI is linked not only to the technological infrastructure, but also to

the readiness, training, and positive attitude of employees towards change (Jöhnk et al., 2021).

RQ7: Do human factors mediate the relationship between technological, organizational, and environmental factors and the adoption of AI?

The answer is clearly positive. In all three mediation analyses, human factors acted as a statistically significant mediator. For technological factors, the indirect effect was .6993. For organizational factors it was .3469. For environmental factors it was .5929. In all three cases, the bootstrap confidence intervals did not contain zero, while the direct effects were not statistically significant. This finding is perhaps the most important theoretical conclusion of the study. It shows that external and internal conditions do not alone lead to the intention of adoption. They must first go through the way they are perceived by employees. Technology, strategy, resources, competition, or regulations come into play when they produce a positive attitude, confidence, a sense of competence, and a readiness to change. In this sense, the human factor is the crucial intermediate mechanism that transforms the context into intention. This result is directly linked to the modern perception of AI as a socio-technical system. The literature no longer treats technology as a neutral tool, but as a system that acquires meaning through organizational structures, human perceptions, and usage practices (Smit & Eybers, 2022; Smit, Eybers, & Van der Merwe, 2024; Uren & Edwards, 2023). In this direction, the present research does not negate the importance of technological, organizational and environmental factors. Instead, it shows that their effect is real, but indirect.

RQ8: Do technological, organizational, or environmental factors modify the relationship between human factors and AI adoption?

The findings indicate that there is no statistically significant modifying effect. The interaction term Human $\times$ Technological was not significant ($\beta = -.0291$, $p = .7833$), as were the term Human $\times$ Organizational ($\beta = -.0906$, $p = .2654$) and the term Human $\times$ Environmental ($\beta = -.0993$, $p = .2911$). In all cases, the change in R^2 due to the interaction was practically negligible. This means that the influence of human factors on adoption intention remains strong regardless of the level of technological readiness, organizational

support or external pressure. This is a particularly interesting finding, because it shows that the human factor is not only the main predictor, but also the most stable. Its importance is not substantially strengthened or weakened by the other factors. In other words, when employees are positive, ready, and willing, adoption intent remains high. When they are not, the rest of the conditions are not enough to overturn this picture. In practice, this is of great importance. It shows that interventions to enhance adoption must start with education, building trust and managing change. Improving the technological infrastructure alone, or strategy alone, does not seem enough if employees are not psychologically and cognitively ready (Amin et al., 2025; Baptista & Pereira, 2025; Osman et al., 2025; Rong et al., 2025 ;Zhang et al., 2023).

RQ9: To what extent are the demographic and professional characteristics of the participants related to the intention to adopt AI?

Most demographic and occupational characteristics did not show statistically significant differences. No significant differences were found in terms of gender ($p=.336$), age ($F=1,052$, $p=.384$), years of work experience ($F=.511$, $p=.676$), education level ($F=1,055$, $p=.389$), and job position ($F=.196$, $p=.822$). In contrast, significant differences were found in business size ($F=3,475$, $p=.018$), previous experience of using AI at work ($t=2,987$, $p=.003$, $d=.559$), and level of ICT digital skills ($F=3,647$, $p=.015$). Especially in digital skills, people with good or excellent skills had a higher adoption intention than those with minimal skills. This result is of particular importance. It shows that the intention to adopt AI does not depend so much on classic socio-demographic characteristics, as on the functional proximity of the worker to the technology. In other words, it is not gender, age or degree that make the difference, but previous experience and real digital skills. This is consistent with the technology acceptance literature, where self-efficacy and facilitating conditions are closely linked to use intention (Nguyen et al., 2024). In organizational terms, it means that familiarity builds acceptance. Equally interesting is the finding about the size of the business. Employees in much smaller companies showed lower adoption intention than those working in enterprises with 401–1000 employees. This can reasonably be linked to resource availability, infrastructure, organizational maturity, and the ability to invest systematically in AI. The conclusion, therefore, is that the adoption of AI is not

differentiated by fixed individual characteristics, but by the degree of exposure, practical familiarity and organizational readiness.

5. Conclusions-Theoretical and Practical Implications, Limitations and Future Research

5.1. Conclusions

Initially, the survey showed that employees recognize the potential of AI to a significant extent. AI seems to be linked, in the consciousness of participants, to improving performance, reducing errors, enhancing service quality and broader modernization of work. At the same time, however, there is no uncritical acceptance. Participants have reservations about issues such as data security, the practical integration of technology into existing systems, and the extent to which they can trust its results in everyday professional practice. This data shows that the insurance sector is in a phase of transition. AI is no longer seen as something foreign, but neither is it a fully established and mature practice.

One of the most important conclusions of the study is that the intention to adopt AI appears particularly high. Most employees state that they are willing to use AI tools in the near future, gradually increase their use and integrate them more into their daily work. This intention is particularly important, because it shows that there is fertile ground for further diffusion of technology in the insurance sector. However, high intention does not automatically mean full or effective adoption. In order to transform the intention into real utilization, appropriate organizational conditions, practical support and substantial support of employees are required.

At the level of correlations, it was found that all key factors are positively associated with the intention to adopt AI. This means that the adoption of AI is not a product of a single factor, but the result of a multi-dimensional interaction. However, the intensity of these relationships was not the same. Human factors emerged as the strongest dimension, which is perhaps the most substantial finding of the research. Employees' attitudes, their willingness to learn, their familiarity with change, their perception of the benefits of AI, but also the trust they show towards it, seemed to influence adoption intention more than any other variable.

The above effect was further enhanced by regression, where human factors emerged as the only consistently strong and statistically significant direct predictor of adoption intention. In contrast, technological, organizational and environmental factors, although positively correlated with correlation-level intention, did not maintain a statistically significant direct effect when examined simultaneously in the same model. This finding leads to a clear conclusion: the success of the adoption of AI in the insurance industry is ultimately not judged only by the capabilities of the technology or by the general organizational and environmental conditions. It is mainly judged by whether the employees themselves are ready to accept it, learn it, trust it and use it in a meaningful way.

An equally important conclusion is that human factors not only function as a direct predictive mechanism, but also as a crucial mediator. The mediation analysis showed that technological, organizational and environmental factors influence adoption intention mainly indirectly, through their effect on human factors. This means that the technological infrastructure, management strategy, external market pressures or regulatory requirements only gain real power when they are translated into positive perceptions, a sense of competence, security and trust on the part of employees. In other words, the human dimension is the key mechanism that transforms the organizational and technological framework into a real adoption intention.

At the same time, the research showed that technological, organizational and environmental factors do not substantially modify the relationship between human factors and adoption intention. This finding is of particular importance because it shows that the impact of the human dimension remains strong and stable, regardless of the level of technological readiness, organisational support or external pressure. So, when employees are positive, qualified, and willing to adapt, adoption intention is steadily strengthened. Conversely, when this readiness is absent, the other conditions alone are not enough to lead to meaningful acceptance.

From demographic and occupational characteristics, it emerged that classic variables, such as gender, age, level of education, job position and years of service, do not substantially differentiate the adoption intention. On the contrary, previous experience of using AI, the level of digital skills and, to a certain extent, the size of the business seem to be more important. This result is particularly significant, because it shows that the adoption of AI is not so much linked to fixed personal characteristics, as to the degree of

exposure to technology, practical familiarity and real possibilities of participation in a digitally mature environment.

Overall, the research leads to the conclusion that the insurance industry in Athens shows clear momentum in terms of the adoption of AI, but this dynamic is not yet fully transformed into a mature and systematic organizational practice. Employees recognize the benefits of AI and show a willingness to move in this direction. At the same time, however, gaps remain evident in terms of education, trust, participation and organizational preparation. Therefore, AI cannot be treated as a technological investment alone. It needs to be approached as a process of organizational change, which requires support, cultivation of skills and strengthening the psychological readiness of employees.

The main final conclusion of this study is that the adoption of AI in the insurance industry is primarily a human issue. Technology, resources, strategies, and external pressures are prerequisites, but they are not enough on their own. The real success of adoption will depend on whether insurance companies are able to create an environment of trust, learning, participation and gradual adaptation. This seems to be the most critical condition for the sustainable integration of AI into the daily operation of the industry.

5.2. Implications of the research

This research aspires to contribute substantially to the understanding of the adoption of AI in the insurance industry, as it examines the issue through the prism of the employees themselves. This contribution is particularly important, because the study focuses on real professionals in the sector, in insurance companies in Athens, and captures a modern picture of how AI is perceived in an environment that is in a phase of digital transition. In this way, the research does not stay at a general theoretical level, but offers empirical data for a specific professional field, where the use of AI is becoming increasingly important.

The contribution of research is also theoretical. Although the initial framework was based on technological, organisational and environmental factors, the results showed very clearly that the human factor is at the core of the adoption intention. Attitudes, trust, knowledge, willingness to learn and readiness to adapt proved to be more decisive than any other dimension. Thus, the study reinforces the view that the adoption of AI is not only a technological or organizational issue, but primarily a human and socio-technical process. This finding adds value to the relevant literature, because it shows that even when

there are technological possibilities or external pressures, the real intention to use is ultimately formed at the level of the employee himself.

Another contribution of the research is its analytical approach. The study was not limited to describing attitudes or simple correlations, but proceeded to a more complex investigation of the relationships between the variables. By regression, mediation, and modification, it has been possible to see not only what factors are related to adoption intent, but also how they work. The fact that human factors mediate the relationship between technological, organizational and environmental factors with adoption intention is one of the most important findings of the study. At the same time, the finding that technological, organizational and environmental factors do not significantly modify the relationship between human factors and adoption intention gives a more mature and detailed picture of how the acceptance of AI works in the insurance sector.

In addition, research has a clear practical contribution. The results show that it is not enough for insurance companies to invest only in technological tools. They also need to invest in their people. The high adoption intention recorded is encouraging, but is accompanied by obvious gaps in training, trust and organizational support. Therefore, the study offers organizations a clear direction: successful integration of AI requires a combination of technological readiness, organizational support, and systematic enhancement of the human dimension.

5.3. Limitations and future research avenues

Despite the importance of the findings, the present study has some limitations that must be taken into account when interpreting them. The first concerns the sample and the possibility of generalizing the results. The survey was carried out on 120 employees of insurance companies from the area of Athens, Attica, with non-probabilistic convenience sampling and avalanche data. This means that, although the sample is considered sufficient for the statistical analyses applied, the findings cannot be considered fully representative for the entire insurance sector in Greece. They mainly reflect the specific geographical and professional reality

A second limitation concerns the design of research. The study is cross-sectional and based on data collected over a specific time period. For this reason, it captures a snapshot of the participants' perceptions and does not allow the monitoring of their

evolution over time. In addition, the data comes from self-reports through a questionnaire. This means that the answers are based on the personal perceptions and assessments of the employees and not on the observation of real behavior in the work environment. Therefore, they are likely to be influenced by subjectivity, socially desirable responses, or different levels of understanding of the questions.

Additionally, the research focused on adoption intent rather than the actual use of AI over time. This element is essential, because intention is a strong indication of readiness, but it is not always the same as the real, systematic and effective use of a technology in practice. It is therefore possible that the high intent recorded does not automatically translate into a correspondingly high level of implementation, especially if gaps remain in terms of infrastructure, education and guidance.

It should also be noted that the general purpose of the study was also linked to issues of organizational efficiency and quality of services. However, in the empirical part, these dimensions were not measured with objective performance indicators, but were mainly reflected through the perceptions of employees for the improvement of performance and quality. This limits the ability to draw safe conclusions about the actual organizational impact of AI at the level of measurable results.

Another limitation is linked to the research tool itself. Although most scales showed satisfactory to very high reliability, the technological dimension showed lower internal consistency compared to the others. This probably indicates that this factor includes heterogeneous aspects, such as utility, security, compatibility and complexity, which are not easily condensed into a single one-dimensional scale. Consequently, findings specific to the technological dimension need more attention.

An additional limitation of this research is that no exploratory factorial analysis was performed to check the internal structure of the research tool. Although the dimensions of the questionnaire were formed based on a theoretical framework and previous literature, the present study did not empirically examine whether the individual items are grouped into the corresponding latent factors in the specific sample. Factorial analysis is an important method for gathering evidence of internal structure validity in questionnaire-type research tools (Knekta et al., 2019; Watkins, 2018). However, due to the relatively limited sample size in relation to the number of items, the application of a total EFA may lead to an unstable or difficult to interpret factorial solution. Therefore, the findings of this research should be interpreted with caution as to the factorial validity of

the tool, while future surveys with a larger sample could further examine its structure through exploratory and/or confirmatory factor analysis.

At the research level, the present study opens several directions for future investigation. Initially, it would be useful to carry out similar surveys with a larger and more representative sample from different geographical areas of Greece, in order to check whether the findings are repeated beyond the Attica region. It would also be particularly interesting to make comparisons between small and large companies, between different functional divisions, but also between insurance sectors, such as general and life insurance. This will allow for a more accurate mapping of differences in organisational maturity and actual readiness for adoption.

Additionally, future studies could adopt a longitudinal design to examine how employee attitudes and behaviors evolve as AI is more systematically integrated into their work. A blended methodological approach, combining quantitative and qualitative data, could also shed light on deeper issues, such as fears, resistances, expectations, and practical experiences of employees. Finally, it would be particularly useful to measure not only intent, but also the actual use of AI, as well as its impact on specific indicators of performance, service quality, and productivity. At the same time, the technological dimension of the tool could be reconfigured and re-examined in a larger sample, with the aim of further enhancing its measurement accuracy.

5.4. Final remarks

Based on the findings of the research, on a practical level it appears that insurance companies need to approach AI not only as a technological investment, but as an overall process of organizational change. The emphasis should be primarily on education, fostering trust, and creating a positive climate towards the use of AI. Employees showed a high willingness to learn and a positive intention to use the technology, but at the same time they stated limited experience, insufficient training and cautious confidence in its results. This means that organizations need to invest in targeted training programs, hands-on familiarity with AI tools, and a gradual introduction of applications that will allow employees to gain a sense of competence and control.

At the same time, it is important for insurance companies to formulate a clear strategy for AI and link it to their daily operations. Management needs to give clear

direction, secure resources and time, encourage employee participation, and incorporate their views into the change process. Research has shown that general organizational support is recognized, but in many cases does not translate into adequate mentoring or systematic training. For this reason, it is proposed to create small pilot applications, evaluate the user experience in real conditions and gradually scale the applications that prove to be functional and acceptable. Particular attention is also needed to the issues of compatibility, data protection and organizational readiness, especially in smaller businesses that show lower adoption intention.

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Appendix A: “Questionnaire”

Dear Participant,

You are invited to take part in this research study as part of a dissertation project for the MBA program at the Hellenic Open University (HOU).

The purpose of this research is to explore the adoption and implementation of Artificial Intelligence (AI) within the insurance industry, with a focus on understanding the opportunities, challenges, and practical impacts of AI integration in business operations.

Your participation in this questionnaire is entirely voluntary and all responses will be kept strictly confidential. The data collected will be used solely for academic purposes and will be anonymized in any reports or publications. The questionnaire will take approximately 5 minutes to complete.

There are no right or wrong answers — your honest opinions and experiences are extremely valuable to this research.

For any further information or inquiries, please feel free to contact me.

Thank you for your time and contribution to this study

Sincerely,
Konstantina Kaponi
email: std166633@ac.eap.gr
tel: 6906936581

Part A: Demographics

1. Gender:

- Male ☐
- Female ☐
- Other ☐

2. Age:

- Under 25 ☐
- 25–34 ☐

- 35–44 ☐
- 45–54 ☐
- 55 and over ☐

3. How long have you been working in the insurance sector?

- Less than 1 year ☐
- 1–5 years ☐
- 6–10 years ☐
- Over 10 years ☐

4. Highest educational qualification:

- Secondary Education ☐
- Vocational Institute (IEK) ☐
- University Degree ☐
- Master's ☐
- Doctorate ☐
- Other ☐

5. Job position:

- Director/Deputy Director ☐
- Supervisor ☐
- Staff ☐

B. Your company

6. Number of employees

C. AI tools - skills

7. Do you have previous experience using AI at work?

- Yes ☐

- No ☐

8. Do you use any of the AI tools below (you can choose more than one answers)

- Google AI
- Open AI
- Microsoft Research
- Google Cloud
- Amazon Web service
- Human AI/Open AI Gym
- Other
- I do not use AI tools

9. How would you assess your ICT (Information & Communication Technology) skills?

- Minimal ☐

- Basic ☐

- Good ☐

- Excellent ☐

2.6.1 Technological Factors

2.6.1.1 Scope and Potential of AI

1. AI can increase my work performance.

2. AI can reduce errors in my work.
3. AI can improve the quality of services we offer.
4. AI can automate many of my daily tasks.

2.6.1.2 Data Security and Privacy

5. I worry about data security when using AI.

2.6.1.3 Compatibility with Existing Systems

6. AI is easy to use.
7. AI is compatible with our existing systems.
8. I am concerned about the complexity of AI.

2.6.2 Organizational Factors

2.6.2.1 Organizational Culture and Strategy

9. AI adoption is part of our company's strategy.
10. The company encourages continuous learning and skill development in AI.
11. Our company has a clear policy for using AI.

2.6.2.2 Management Support and Leadership

12. Company management supports the use of AI.
13. Management provides the necessary resources and time during working hours to adopt AI.
14. There is clear guidance from management on adopting AI.
15. I feel management values employees' opinions about AI.

2.6.2.3 Training and Skill Development

16. The company provides sufficient AI training.
17. I have participated in AI training programs.

2.6.3 Environmental Factors

2.6.3.1 Legal and Regulatory Framework

18. The legal and regulatory framework supports AI adoption.

19. Data protection regulations affect AI adoption.

2.6.3.2 Economic Factors

20. The company's financial situation supports investment in AI.

2.6.3.3 Market Trends and Competition

21. Market competition drives AI adoption.

22. AI is necessary to maintain our competitive advantage.

23. Social acceptance of AI affects its use in our company.

24. Our customers expect us to use AI to improve services.

25. Technological developments mandate AI adoption.

2.6.4 Human Factors

2.6.4.1 Employee Perceptions and Attitudes Toward AI

26. I have a positive opinion about AI.

27. I am willing to learn more about AI.

28. I am excited about AI's capabilities.

29. In my opinion, the benefits of AI adoption outweigh the potential risks or downsides.

2.6.4.2 Experience and Knowledge in AI

30. I have sufficient knowledge and experience in AI.

31. I have participated in AI training programs (also organizational but relevant to human knowledge).

2.6.4.3 Response to Change

32. I believe I need more training to fully leverage AI in my job.

33. I feel comfortable with the changes AI brings to my work.

34. I feel AI might replace some of my tasks.

35. I feel AI use may lead to job losses.

2.6.4.4 Trust in AI and Its Results

36. I trust the outcomes produced by AI.

37. I believe AI can help in making better decisions.

2.6.4.5 Personal and Professional Development through AI

38. I believe AI can contribute to my professional development.

39. I believe AI can improve my work experience.

Intention to Adopt AI

40. I intend to start using AI tools in my work soon.

41. I plan to use AI regularly in the near future.

42. I am willing to adopt new AI technologies when they become available.

43. I expect to increase my use of AI tools over time.

44. If the company provides AI tools, I will actively use them.

45. Using AI is something I see myself doing in my daily work.

46. I am likely to adopt AI because I believe it will benefit my work.

Appendix B: “Tables”

Table 13. *Mediation analysis*

```
*****
**
Model : 4
Y : Intention to Adopt AI
X : Technological Factors
M : Human Factors

Sample
Size: 120

*****
**
OUTCOME VARIABLE:

Human Factors

Model Summary
R R-sq MSE F df1 df2 p
.5318 .2828 .2437 46.5244 1.0000 118.0000 .0000

Model
coeff se t p LLCI ULCI
constant 1.1462 .3564 3.2159 .0017 .4404 1.8520
Technological
Factors.6777 .0994 6.8209 .0000 .4810 .8745

*****
**
OUTCOME VARIABLE:
Intention to Adopt AI

Model Summary
R R-sq MSE F df1 df2 p
.8463 .7163 .1528 147.6744 2.0000 117.0000 .0000

Model
coeff se t p LLCI ULCI
constant .0643 .2943 .2184 .8275 -.5186 .6472
Technological
Factors .0673 .0929 .7246 .4702 -.1167 .2513
Human Factors 1.0319 .0729 14.1561 .0000 .8875 1.1763
```

***** DIRECT AND INDIRECT EFFECTS OF X ON Y

Direct effect of X on Y
Effect se t p LLCI ULCI
.0673 .0929 .7246 .4702 -.1167 .2513

Indirect effect(s) of X on Y:
Effect BootSE BootLLCI BootULCI
Human
Factors .6993 .1224 .4656 .9447

***** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS

OUTCOME VARIABLE:
Human Factors

Coeff BootMean BootSE BootLLCI BootULCI
constant 1.1462 1.1511 .3497 .4809 1.8459
Technological
Factors .6777 .6764 .0951 .4875 .8585

OUTCOME VARIABLE:
Intention to Adopt AI

Coeff BootMean BootSE BootLLCI BootULCI
constant .0643 .0821 .2661 -.4458 .6052
Technological
Factors .0673 .0692 .1054 -.1479 .2647
Human
Factors 1.0319 1.0256 .0947 .8308 1.2025

Table 14. Mediation analysis

**

Model : 4
Y : Intention to Adopt AI
X : Organizational Factors
M : Human Factors

Sample
Size: 120

**

OUTCOME VARIABLE:
MO_AP

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4089	.1672	.2830	23.6947	1.0000	118.0000	.0000

Model

coeff	se	t	p	LLCI	ULCI
constant	2.3900	.2448	9.7648	.0000	1.9053 2.8747

Organizational

Factors	.3312	.0680	4.8677	.0000	.1965 .4659
---------	-------	-------	--------	-------	-------------

**

OUTCOME VARIABLE:
Intention to Adopt AI

Model Summary

R	R-sq	MSE	F	df1	df2	p
.8459	.7155	.1532	147.1202	2.0000	117.0000	.0000

Model

coeff	se	t	p	LLCI	ULCI
constant	.1605	.2422	.6627	.5089	-.3191 .6401

Organizational

Factors	.0251	.0549	.4573	.6483	-.0836 .1337
---------	-------	-------	-------	-------	--------------

Human

Factors	1.0473	.0677	15.4611	.0000	.9132 1.1815
---------	--------	-------	---------	-------	--------------

***** DIRECT AND INDIRECT EFFECTS OF X ON Y

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.0251	.0549	.4573	.6483	-.0836	.1337

Indirect effect(s) of X on Y:

Effect	BootSE	BootLLCI	BootULCI
--------	--------	----------	----------

Human

Factors	.3469	.0792	.1983 .5084
---------	-------	-------	-------------

***** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS

OUTCOME VARIABLE:

Human

Factors

	Coeff	BootMean	BootSE	BootLLCI	BootULCI
constant	2.3900	2.3849	.2469	1.9108	2.8633
Organizational Factors	.3312	.3325	.0677	.1990	.4616

OUTCOME VARIABLE:
Intention to Adopt AI

	Coeff	BootMean	BootSE	BootLLCI	BootULCI
constant	.1605	.1646	.2924	-.3882	.7312
Organizational Factors	.0251	.0282	.0668	-.1037	.1578
Human Factors	1.0473	1.0432	.0768	.8925	1.1870

Table 15. Mediation analysis

**

Model : 4
Y : Intention to Adopt AI
X : Environmental Factors
M : Human Factors

Sample
Size: 120

**

OUTCOME VARIABLE:
Human Factors

Model Summary
R R-sq MSE F df1 df2 p
.5950 .3540 .2195 64.6585 1.0000 118.0000 .0000

	coeff	se	t	p	LLCI	ULCI
constant	1.4377	.2671	5.3825	.0000	.9087	1.9666
Environmental Factors	.6043	.0752	8.0410	.0000	.4555	.7531

**

OUTCOME VARIABLE:

Intention to Adopt AI

Model Summary

R R-sq MSE F df1 df2 p
.8498 .7222 .1496 152.0870 2.0000 117.0000 .0000

Model

coeff se t p LLCI ULCI
constant .0122 .2461 .0495 .9606 -.4752 .4995
Environmental
Factors .1346 .0772 1.7437 .0838 -.0183 .2875
Human
Factors .9811 .0760 12.9102 .0000 .8306 1.1316

***** DIRECT AND INDIRECT EFFECTS OF X ON Y

Direct effect of X on Y

Effect se t p LLCI ULCI
.1346 .0772 1.7437 .0838 -.0183 .2875

Indirect effect(s) of X on Y:

Effect BootSE BootLLCI BootULCI
Human
Factors .5929 .1015 .4070 .8026

***** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS

OUTCOME VARIABLE:

Human Factors
Coeff BootMean BootSE BootLLCI BootULCI
constant 1.4377 1.4336 .2669 .8960 1.9422
Environmental
Factors .6043 .6051 .0724 .4651 .7478

OUTCOME VARIABLE:

Intention to Adopt AI
Coeff BootMean BootSE BootLLCI BootULCI
constant .0122 .0332 .2729 -.5032 .5766
Environmental
Factors .1346 .1362 .0773 -.0187 .2814
Human
Factors .9811 .9739 .0930 .7837 1.1448

Table 16. Moderation analysis

**

Model : 1

Y : Intention to Adopt AI

X : Human Factors

W : Technological Factors

Sample

Size: 120

**

OUTCOME VARIABLE:

Intention to Adopt AI

Model Summary

R R-sq MSE F df1 df2 p

.8464 .7164 .1540 97.6974 3.0000 116.0000 .0000

Model

coeff se t p LLCI ULCI

constant -.2819 1.2899 -.2185 .8274 -2.8367 2.2730

Human

Factors 1.1335 .3756 3.0176 .0031 .3895 1.8774

MO_TP .1679 .3765 .4459 .6565 -.5779 .9136

Int_1 -.0291 .1057 -.2757 .7833 -.2385 .1803

Product terms key:

Int_1 : Human Factors x Technological Factors

Test(s) of highest order unconditional interaction(s):

R2-chng F df1 df2 p

X*W .0002 .0760 1.0000 116.0000 .7833

Focal predict: Human

Factors (X)

Mod var: Technological

Factors (W)

Data for visualizing the conditional effect of the focal predictor:

Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/

Human

Factors Technological

Factors Intention

to Adopt AI.

BEGIN DATA.

3.0000 3.1700 3.3735
3.5714 3.1700 3.9684
4.1171 3.1700 4.5365
3.0000 3.5000 3.4000
3.5714 3.5000 3.9894
4.1171 3.5000 4.5523
3.0000 4.0000 3.4403
3.5714 4.0000 4.0213
4.1171 4.0000 4.5763

END DATA.

GRAPH/SCATTERPLOT=

Human

Factors WITH Intention

to Adopt AI BY Technological

Factors.

***** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS

OUTCOME VARIABLE:

Intention to Adopt AI

	Coeff	BootMean	BootSE	BootLLCI	BootULCI
constant	-.2819	-.1433	1.3534	-2.6829	3.1837
Human					
Factors	1.1335	1.0974	.3812	.1914	1.8121
Technological					
Factors	.1679	.1350	.4028	-.8202	.8771
Int_1	-.0291	-.0207	.1072	-.2175	.2409

Table 17. Moderation analysis

**

Model : 1

Y : Intention to Adopt AI

X : Human Factors

W : Organizational Factors

Sample

Size: 120

**

OUTCOME VARIABLE:

Intention to Adopt AI

Model Summary

R R-sq MSE F df1 df2 p

.8477 .7185 .1529 98.7093 3.0000 116.0000 .0000

Model 1

coeff se t p LLCI ULCI

constant -.9715 1.0400 -.9341 .3522 -3.0314 1.0884

Human

Factors 1.3661 .2928 4.6661 .0000 .7862 1.9459

Organizational

Factors .3512 .2965 1.1845 .2387 -.2361 .9385

Int_1 -.0906 .0810 -1.1191 .2654 -.2510 .0698

Product terms key:

Int_1 : MO_AP x MO_OP

Test(s) of highest order unconditional interaction(s):

R2-chng F df1 df2 p

X*W .0030 1.2524 1.0000 116.0000 .2654

Focal predict: Human Factors (X)

Mod var: Organizational Factors (W)

Data for visualizing the conditional effect of the focal predictor:

Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/

Human

Factors Organizational

Factors Intention

to Adopt AI.

BEGIN DATA.

3.0000 2.7778 3.3472

3.5714 2.7778 3.9840

4.1171 2.7778 4.5921

3.0000 3.5556 3.4089

3.5714 3.5556 4.0054

4.1171 3.5556 4.5751

3.0000 4.2222 3.4618

3.5714 4.2222 4.0238

4.1171 4.2222 4.5605

END DATA.

GRAPH/SCATTERPLOT=

Human

Factors WITH Intention

to Adopt AI BY Organizational

Factors

***** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS

OUTCOME VARIABLE:

MO_YTN

	Coeff	BootMean	BootSE	BootLLCI	BootULCI
constant	-.9715	-1.3113	1.7700	-4.9960	1.7085
Human					
Factors	1.3661	1.4502	.4650	.6402	2.4189
Organizational					
Factors	.3512	.4529	.4929	-.3986	1.4660
Int_1	-.0906	-.1157	.1269	-.3772	.1062

Table 18. Moderation Analysis

**

Model : 1

Y : Intention to Adopt AI

X : Human Factors

W : Environmental Factors

Sample

Size: 120

**

OUTCOME VARIABLE:

Intention to Adopt AI

Model Summary

R R-sq MSE F df1 df2 p

.8514 .7249 .1494 101.8744 3.0000 116.0000 .0000

Model

coeff se t p LLCI ULCI

constant -1.1956 1.1650 -1.0262 .3069 -3.5030 1.1119

Human

Factors 1.3224 .3306 4.0001 .0001 .6676 1.9771

Environmental

Factors .4917 .3454 1.4234 .1573 -.1925 1.1758

Int_1 -.0993 .0936 -1.0606 .2911 -.2848 .0862

Product terms key:

Int_1 : Human Factors x Environmental Factors

Test(s) of highest order unconditional interaction(s):

R2-chng F df1 df2 p

X*W .0027 1.1248 1.0000 116.0000 .2911

Focal predict: Human Factors (X)

Mod var: Environmental Factors (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

```
DATA LIST FREE/
Human
Factors Environmental
Factors Intention
to Adopt AI.
BEGIN DATA.
3.0000 3.0000 3.3528
3.5714 3.0000 3.9381
4.1171 3.0000 4.4972
3.0000 3.5000 3.4496
3.5714 3.5000 4.0066
4.1171 3.5000 4.5386
3.0000 4.1250 3.5707
3.5714 4.1250 4.0922
4.1171 4.1250 4.5903
END DATA.
GRAPH/SCATTERPLOT=
Human Factors WITH Intention to Adopt AI BY Environmental Factors.

***** BOOTSTRAP RESULTS FOR REGRESSION MODEL PARAMETERS
*****

OUTCOME VARIABLE:
Intention to Adopt AI
Coeff BootMean BootSE BootLLCI BootULCI
constant -1.1956 -1.1952 1.3224 -3.8626 1.5081

Human
Factors 1.3224 1.3196 .3719 .5443 2.0664

Environmental
Factors .4917 .4970 .3606 -.2319 1.2274

Int_1 -.0993 -.1000 .0967 -.2945 .0939
```

Table 19. *Group Statistics*

	Gender	N	Mean	Std. Deviation	Std. Error Mean
Intention to Adopt AI	Male	51	4.05	.648	.091
	Female	69	3.92	.782	.094

Table 20. *Independent Samples Test*

		Levene's Test for Equality of Variances				Significance		Mean Difference	Std. Error Difference
		F	Sig.	t	df	One-Sided p	Two-Sided p		
Intention to Adopt AI	Equal variances assumed	.560	.456	.939	118	.175	.349	.126	.134
	Equal variances not assumed			.966	116.379	.168	.336	.126	.131

Table 21. *Independent Samples Effect Sizes*

		Standardizera	Point Estimate	95% Confidence Interval	
				Lower	Upper
Intention to Adopt AI	Cohen's d	.728	.173	-.189	.536
	Hedges' correction	.733	.172	-.188	.532
	Glass's delta	.782	.162	-.202	.524

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Table 22. *ANOVA*

Intention to Adopt AI

	Sum of Squares	df	Mean Square	F	Sig.
<i>Between Groups</i>	2.224	4	.556	1.052	.384
<i>Within Groups</i>	60.782	115	.529		
<i>Total</i>	63.007	119			

Table 23. *ANOVA*

Intention to Adopt AI	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.822	3	.274	.511	.676

Within Groups	62.185	116	.536		
Total	63.007	119			

Table 24. ANOVA

Intention to Adopt AI	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.785	5	.557	1.055	.389
Within Groups	60.221	114	.528		
Total	63.007	119			

Table 25. ANOVA

Intention to Adopt AI	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.210	2	.105	.196	.822
Within Groups	62.796	117	.537		
Total	63.007	119			

Author's Statement:

I hereby declare that, in accordance with article 8 of Law 1599/1986 and article 2.4.6 par. 3 of Law 1256/1982, this thesis/dissertation is solely a product of personal work and does not infringe any intellectual property rights of third parties and is not the product of a partial or total plagiarism, and the sources used are strictly limited to the bibliographic references.