

Article

Artificial Intelligence in Marine Insurance Risk Assessment: Evidence from the Moroccan Maritime Sector

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Abstract

This study examines the role of artificial intelligence (AI) in marine insurance within the Moroccan maritime sector. Drawing on Dynamic Capabilities Theory, the study investigates the relationships among AI Adoption, Risk Assessment Accuracy, Fraud Detection Capability, Claim Processing Efficiency, and Customer Trust, while also examining the mediating role of these operational capabilities. A quantitative survey was conducted among maritime and insurance professionals operating within the Tangier Med and Casablanca port ecosystems, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that AI Adoption is positively associated with Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency. These operational capabilities are also positively associated with Customer Trust and function as significant mediating pathways between AI Adoption and stakeholder confidence. The study contributes to the emerging literature on AI applications in marine insurance by providing empirical evidence from an emerging maritime economy and offers theoretical and practical implications for insurers, maritime operators, and policymakers.

Keywords: artificial intelligence; marine insurance; risk assessment; maritime risk management; structural equation modeling

1. Introduction

The maritime transport sector plays a pivotal position in the international trade system, delivering over 90% of global goods flows while supporting the functioning of supply chains worldwide (Verschuur et al., 2022). With the development of maritime logistics systems in the global economy, this sector has become increasingly vulnerable to both operational and financial risks. Cargo damage, accidents, delays, incidents of piracy and fraudulent documentation are just some of the uncertainties associated with maritime operations (Gülmez et al., 2023). Under these circumstances, marine insurance acts as a means of protecting maritime trade by reducing costs associated with these risks and ensuring the continued flow of trade. Traditionally, assessing maritime risks is based mainly on historical data, professional opinions and general actuarial methods, requiring extensive data processing and analysis (Bunwaree, 2025). Such approaches have supported the growth of the insurance sector for years, yet the complexity of maritime logistics and the rapidly increasing volume of shipping data are making conventional risk



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assessment methods increasingly insufficient. As maritime transport systems become more interconnected and data-intensive, insurance companies find themselves compelled to adopt powerful analytical tools capable of supporting greater speed and perceived quality in risk assessment processes (A. E. El Moussaoui, 2024).

Marine insurance differs substantially from other insurance sectors because maritime risks are shaped by highly dynamic operational conditions, including vessel movements, cargo characteristics, cargo documentation processes, weather conditions, port congestion, geopolitical disruptions, cyber threats, maritime fraud, and complex cross-border claims procedures (Dunt, 2015). The evaluation of such risks requires the integration of heterogeneous and real-time data originating from multiple stakeholders and operational systems, making maritime risk assessment one of the most complex activities within the insurance industry (Durlik et al., 2024). Consequently, the growing complexity of maritime logistics systems has intensified the need for more advanced analytical approaches capable of supporting accurate and timely insurance decisions.

Over the past decade, artificial intelligence (AI) has emerged as one of the most influential technologies supporting data-driven decision-making across industries (Wu et al., 2025). AI technologies allow organizations to analyze and process large volumes of heterogeneous data, identify hidden patterns, and generate predictions that would be difficult to obtain using conventional analytical methods. In the insurance sector, AI-based solutions have increasingly been employed to support underwriting decisions, automate claims management processes, and strengthen fraud detection mechanisms (Alamuri et al., 2025). Such technological advances are particularly relevant to marine insurance, where effective risk assessment requires the analysis of multiple variables, including vessel characteristics, cargo specifications, navigation routes, weather conditions, and terminal operations (Durlik et al., 2024; Yu et al., 2025). The integration of AI-based analytics into insurance risk management systems therefore has the potential to support more effective risk assessment processes, stronger fraud detection capabilities, and more efficient claims processing activities (Rahman, 2025).

From a theoretical perspective, this study draws on Dynamic Capabilities Theory, which argues that organizations achieve superior performance by developing capabilities to sense environmental changes, seize emerging opportunities, and reconfigure resources in response to evolving market conditions (Teece et al., 1997). In the context of marine insurance, AI adoption can be viewed as a strategic technological resource, while risk assessment accuracy, fraud detection capability, and claims processing efficiency represent critical operational capabilities through which AI may generate organizational value. Customer trust, in turn, represents a key strategic outcome of these enhanced capabilities. Dynamic Capabilities Theory therefore provides a coherent foundation for explaining the relationships examined in this study.

While interest in AI within the insurance industry has grown considerably, the application of AI to marine insurance remains relatively underexplored in the academic literature. Existing studies have primarily focused on AI adoption in life insurance, health insurance, financial risk assessment, and general insurance services, where AI has been associated with higher levels of underwriting accuracy, customer service quality, claims automation, and operational efficiency (Rao & Soofastaei, 2025). Previous studies have concentrated mainly on digitally transforming insurance markets, with a particular focus on life insurance, health insurance, and financial risk insurance. Furthermore, although recent research has explored AI applications in maritime transportation, vessel monitoring, and maritime risk management, relatively little empirical evidence exists regarding how AI influences operational performance and customer trust within marine insurance organizations. Most empirical studies investigating AI implementation in maritime insurance

have also been conducted in developed economies such as the United States, Germany, the United Kingdom, and France, leaving a limited understanding of how AI-enabled capabilities contribute to marine insurance performance in emerging maritime economies (Miller et al., 2025; Bahadoran-Baghbaderani et al., 2025).

Another important gap concerns the mechanisms through which AI adoption translates into organizational outcomes. Previous research has largely emphasized the technological benefits of AI while paying limited attention to how AI contributes to specific operational capabilities and how these capabilities subsequently influence customer trust. While existing studies frequently assume that differences in operational capabilities explain the benefits associated with AI adoption, empirical evidence regarding the indirect relationships through which AI-enabled capabilities contribute to customer trust remains limited, particularly within marine insurance settings. Unlike previous studies that have primarily examined AI applications in general insurance or maritime operations separately, this study investigates both the direct effects of AI adoption on risk assessment accuracy, fraud detection capability, claims processing efficiency, and customer trust, as well as the mediating role of these operational capabilities in linking AI adoption to customer trust. The present study focuses specifically on risk assessment accuracy, fraud detection capability, and claims processing efficiency because these dimensions represent the three core operational functions through which marine insurers evaluate risks, prevent financial losses, and deliver service value to maritime stakeholders.

The Moroccan context provides a particularly relevant empirical setting for investigating these issues. Morocco has emerged as one of Africa's leading maritime and logistics hubs through significant investments in port infrastructure, logistics connectivity, and digital transformation initiatives. Tangier Med has become one of the largest container ports in the Mediterranean and Africa, while Casablanca remains a strategic gateway for international trade (A. E. El Moussaoui, 2025). The increasing complexity and digitalization of maritime operations within these port ecosystems create an appropriate setting for examining the implications of AI adoption in marine insurance.

Accordingly, this study seeks to examine how AI adoption is associated with risk assessment accuracy, fraud detection capability, claims processing efficiency, and customer trust in the Moroccan maritime insurance sector. Focusing on the perceptions of insurance professionals, port operators, and shipping company personnel, the study provides empirical evidence regarding the role of AI in supporting marine insurance operations within an emerging maritime economy.

This paper contributes to the literature in several ways. First, it extends the growing body of research on AI adoption by focusing on the relatively underexplored domain of marine insurance. Second, it applies Dynamic Capabilities Theory to explain how AI-enabled operational capabilities contribute to customer trust. Third, it empirically examines both the direct effects of AI adoption and the indirect pathways through which risk assessment accuracy, fraud detection capability, and claims processing efficiency mediate the relationship between AI adoption and customer trust. Fourth, it provides a theoretically grounded explanation for the role of these operational capabilities as strategic mediating mechanisms linking technological adoption to organizational outcomes. Fifth, it provides empirical evidence from an emerging maritime economy, thereby expanding the geographical scope of existing studies on AI-enabled insurance systems. Finally, the study offers practical insights for insurers, port authorities, shipping companies, and policymakers seeking to leverage AI-based solutions to support maritime risk management and insurance service effectiveness.

The rest of this paper is structured as follows. Section 2 presents a literature review of artificial intelligence in the insurance sector and marine risk management. Section 3

provides the conceptual framework and develops the research hypotheses. Section 4 outlines the research methodology and data analysis procedures. Section 5 presents and discusses the empirical findings. Finally, Section 6 highlights the theoretical and managerial implications, discusses limitations, and suggests directions for future research.

2. Literature Review

2.1. Artificial Intelligence in Marine Insurance Risk Assessment

Marine insurance plays a fundamental role in supporting the continuity and stability of international maritime trade. As maritime transport accounts for the majority of global merchandise exchanges, maritime stakeholders face numerous operational and financial risks that require specialized insurance mechanisms capable of mitigating potential losses (Ibrahim, 2025). Traditionally, marine insurance covers a broad range of risks, including vessel accidents, cargo damage, adverse weather conditions, piracy incidents, operational disruptions, and liabilities arising from maritime transport activities (He et al., 2023). The effective management of such risks is essential not only for insurance companies but also for the overall resilience of global supply chains and international trade networks.

The growing complexity of maritime logistics systems has significantly transformed the nature of maritime risk management. Modern maritime operations generate large volumes of heterogeneous information originating from vessel tracking systems, cargo monitoring technologies, port management platforms, customs procedures, and logistics information systems (Freichel et al., 2022; A. E. El Moussaoui et al., 2025; Wang & Hsu, 2025). Furthermore, maritime risks are increasingly influenced by dynamic factors such as port congestion, geopolitical tensions, cyber threats, supply chain disruptions, environmental uncertainties, and fluctuations in international trade flows (Koray et al., 2025). Consequently, traditional risk assessment approaches based primarily on historical records and actuarial calculations often struggle to capture the real-time complexity of contemporary maritime operations (Perkovič et al., 2024).

These developments have encouraged insurers to explore digital technologies capable of supporting greater effectiveness and precision in risk assessment processes. Among these technologies, artificial intelligence (AI) has emerged as one of the most transformative innovations within financial and insurance services (Bahadoran-Baghbaderani et al., 2025). AI refers to a set of computational techniques that enable machines to simulate human intelligence through learning, pattern recognition, prediction, and decision support functions (T. El Moussaoui et al., 2025). By processing large volumes of structured and unstructured information, AI systems can identify hidden relationships between variables, generate predictive insights, and support more informed decision-making processes.

The adoption of AI has expanded rapidly across multiple insurance sectors. Previous studies have demonstrated that AI has been associated with more effective underwriting decisions in life insurance, more effective patient risk evaluation in health insurance, more accurate credit and financial risk assessments, and greater operational efficiency in general insurance services (Rao & Soofastaei, 2025; Alkhelb & Alshagrawi, 2025). AI-based solutions have also been associated with reductions in processing times, improved customer experiences, and more sophisticated fraud detection mechanisms (Sarna et al., 2025).

The potential value of AI appears particularly significant within marine insurance because maritime risk assessment requires the simultaneous evaluation of multiple interconnected variables. Insurers must analyze vessel characteristics, cargo specifications, navigation routes, weather conditions, terminal operations, historical incidents, and regulatory requirements when determining risk exposure (Ali, 2025; Chen et al., 2025).

AI technologies enable insurers to integrate these diverse data sources into predictive models that may support more accurate and timely risk assessments. By moving beyond

conventional actuarial techniques, AI allows insurers to incorporate real-time operational information into underwriting decisions, thereby supporting the quality of risk evaluation processes (Bhattacharya et al., 2025).

In addition to risk assessment, AI offers important opportunities for supporting fraud detection and claims management activities. Marine insurance transactions often involve multiple stakeholders operating across different jurisdictions, creating complex documentation requirements and increasing the potential for fraudulent behavior (Meggitt, 2024; Naidoo, 2024).

Fraudulent claims, manipulated documentation, and information asymmetries continue to represent significant challenges for insurers (Zhang, 2025). Machine learning algorithms and anomaly detection systems can identify suspicious patterns within claims data, detect inconsistencies across documentation sources, and support the early identification of potentially fraudulent activities (Rahul, 2022; A. E. El Moussaoui et al., 2022; Al-Attar et al., 2025). Such capabilities may be associated with lower financial losses and greater integrity in insurance operations.

Similarly, AI can support claims processing activities by automating document verification procedures, accelerating information retrieval, and supporting decision-making during claims evaluation (Pandiri & Chitta, 2023). Faster and more transparent claims management processes are particularly important in maritime environments, where operational disruptions often generate substantial financial consequences for stakeholders. Consequently, higher levels of claims management efficiency may be associated not only to operational performance but also to greater customer satisfaction and confidence in insurance services (Abuelenin, 2025).

Despite these promising developments, the application of AI in marine insurance remains relatively underexplored compared with other insurance sectors. Existing studies have focused predominantly on digital transformation within life insurance, health insurance, and financial services, while marine insurance has received comparatively limited scholarly attention (Pandey, 2023; Van der Heide & Kohl, 2024). Furthermore, many studies addressing digitalization in maritime contexts have concentrated on shipping operations, smart ports, vessel monitoring systems, and maritime logistics rather than marine insurance itself (Fruth & Teuteberg, 2017; Zou et al., 2025). Consequently, there remains limited empirical evidence regarding how AI adoption influences operational capabilities and stakeholder perceptions within marine insurance organizations. This gap is particularly important given the strategic role of marine insurance in supporting global trade and maritime logistics systems.

2.2. Dynamic Capabilities Theory and AI-Enabled Operational Capabilities

To explain how AI adoption contributes to organizational outcomes in marine insurance, this study adopts Dynamic Capabilities Theory as its principal theoretical foundation. Dynamic Capabilities Theory argues that organizations achieve sustainable competitive advantages not merely through the possession of valuable resources but through their ability to continuously sense environmental changes, seize emerging opportunities, and reconfigure resources in response to evolving market conditions (Teece et al., 1997; Beske, 2012).

The theory is particularly relevant to marine insurance because maritime environments are characterized by high levels of uncertainty, complexity, and information intensity (Lambourdiere & Corbin, 2020). Insurance companies must continuously monitor emerging risks, evaluate changing operational conditions, and adapt decision-making processes to maintain effectiveness. Under such circumstances, technological resources alone are insufficient. Rather, organizational value is generated when these resources are transformed

into operational capabilities that support performance and stakeholder outcomes (Polu et al., 2025).

AI represents a strategic innovation resource that supports insurers' ability to collect, process, and interpret information more effectively. However, the benefits of AI are realized only when organizations develop capabilities that allow them to utilize these technological resources effectively (Olan et al., 2022). Accordingly, this study focuses on three operational capabilities that are particularly relevant to marine insurance: risk assessment accuracy, fraud detection capability, and claims processing efficiency.

Risk assessment accuracy represents the ability of insurers to evaluate maritime risks precisely and consistently using multiple sources of information (Shen et al., 2022; Perkovič et al., 2024). Accurate risk evaluation is essential because insurance decisions directly influence premium calculations, policy conditions, and overall risk management effectiveness. From a Dynamic Capabilities perspective, risk assessment accuracy reflects an organization's sensing capability, as it involves identifying, interpreting, and evaluating risk-related information in complex environments (Herburger et al., 2024).

Fraud detection capability refers to the ability of insurers to identify suspicious transactions, documentation inconsistencies, and fraudulent claims within insurance processes (Meggitt, 2024; Alhuniati & Al-Khasawneh, 2025). Effective fraud detection may help insurers limit financial losses and support operational transparency. Within Dynamic Capabilities Theory, fraud detection capability can be associated with seizing opportunities and mitigating threats by enabling organizations to respond proactively to emerging risks and abnormal patterns (Awolowo et al., 2026).

Claims processing efficiency reflects the speed, accuracy, and effectiveness with which claims are evaluated, verified, and resolved (Rahul, 2022). Efficient claims management is particularly important in marine insurance because delayed settlements may create significant financial and operational consequences for maritime stakeholders. From a Dynamic Capabilities perspective, claims processing efficiency reflects an organization's ability to reconfigure operational processes and allocate resources more effectively in response to customer needs and environmental demands (Apte et al., 2010; Al Mamun et al., 2025).

The selection of these three capabilities is theoretically and practically justified. They represent the core operational functions through which marine insurers create value, manage uncertainty, and deliver reliable services. Moreover, these capabilities correspond closely to the principal stages of the insurance value chain, namely risk evaluation, fraud prevention, and claims management. Consequently, they provide an appropriate theoretical foundation for examining both the direct effects of AI adoption on operational performance and the potential mediating role of these capabilities in linking AI adoption to customer trust.

A critical review of the literature reveals several important research gaps. First, although AI has received considerable attention within insurance and financial services research, empirical investigations focusing specifically on marine insurance remain limited. Second, most studies examining digital transformation in maritime environments concentrate on shipping operations, port management, or logistics systems, leaving marine insurance relatively underrepresented in the literature. Third, previous research has largely emphasized the technological benefits of AI while providing limited insights into the indirect pathways through which AI-enabled operational capabilities may help explain the association between AI adoption and customer trust.

Another important limitation concerns geographical context. Existing studies on AI-enabled insurance solutions have been conducted predominantly in developed economies, while emerging maritime economies remain comparatively underexplored. This limitation

is particularly significant because countries such as Morocco are experiencing rapid growth in maritime trade, logistics infrastructure, and digital transformation initiatives.

To address these gaps, the present study adopts Dynamic Capabilities Theory to examine how AI adoption is associated with three critical operational capabilities—risk assessment accuracy, fraud detection capability, and claims processing efficiency—and how these capabilities influence customer trust within marine insurance services. In addition to examining the direct relationships among these constructs, the study investigates whether risk assessment accuracy, fraud detection capability, and claims processing efficiency mediate the relationship between AI adoption and customer trust. By focusing on the Moroccan maritime sector, the study extends existing knowledge regarding AI-enabled transformation in marine insurance while providing empirical evidence from an important emerging maritime economy. The resulting conceptual framework is presented in Section 3 and serves as the foundation for the development of the research hypotheses.

3. Conceptual Framework and Hypotheses Development

3.1. Conceptual Framework

Digitalization of maritime transport systems has fundamentally transformed the way risks are identified, assessed, and managed across global maritime networks (Raza et al., 2023). Marine insurance currently operates in an increasingly complex environment characterized by uncertainty, large volumes of heterogeneous information, and multiple sources of operational, environmental, financial, and fraudulent risks. Traditional approaches based primarily on historical records, actuarial models, and expert judgment often face limitations in capturing the dynamic and interconnected nature of contemporary maritime operations (Parveen, 2024). Consequently, insurers are increasingly seeking advanced technological solutions capable of supporting risk evaluation processes and more effective decision-making.

Drawing on Dynamic Capabilities Theory, this study proposes that artificial intelligence represents a strategic technological resource capable of supporting organizational capabilities within marine insurance services (Teece et al., 1997). According to this theoretical perspective, organizations achieve superior performance by developing capabilities that enable them to sense environmental changes, seize emerging opportunities, and reconfigure resources in response to evolving market conditions. In highly uncertain and information-intensive environments such as maritime insurance, these capabilities are particularly important because insurers must continuously process new information, evaluate emerging risks, and adapt operational processes to changing circumstances (Kuznetsov, 2026).

AI provides a revolutionary solution for processing real-time, large and heterogeneous data sets from shipping vessels, ports and transportation systems. Using machine learning and predictive analytics, AI can support decision-making in critical insurance processes such as claim assessment, fraud detection and risk management.

Within the proposed framework (Figure 1), AI adoption is conceptualized as the primary technological driver that enables insurers to transform large volumes of operational and environmental data into actionable knowledge. Through machine learning algorithms, predictive analytics, pattern recognition systems, and automated decision-support tools, AI may enhance insurers' ability to analyze complex maritime information and support the effectiveness of core insurance activities (Das, 2024). However, Dynamic Capabilities Theory suggests that technological resources alone do not automatically create organizational value. Rather, value emerges when such resources contribute to the development of operational capabilities that support organizational performance and stakeholder outcomes.

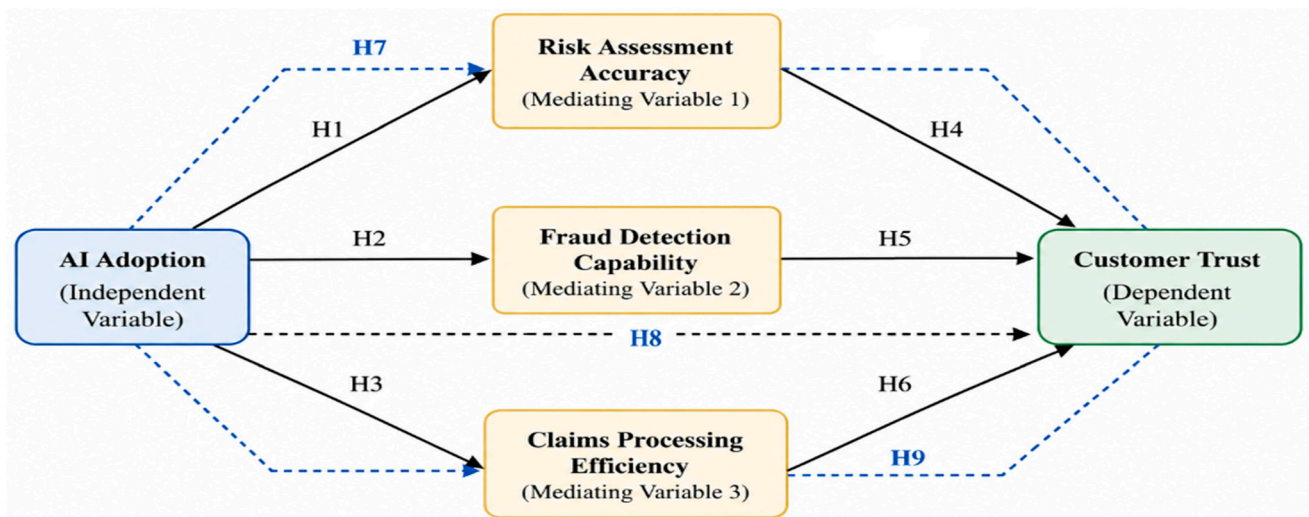


Figure 1. Conceptual framework of AI adoption in marine insurance.

The conceptual framework illustrates how the adoption of AI functions as a technological catalyst influencing three core operational capabilities: (1) Risk assessment accuracy, defined as the ability of insurers to precisely evaluate risks using various integrated data sources (Shen et al., 2022; Perkovič et al., 2024); (2) Fraud detection capability, meaning the potential to identify fraud and suspicious claims in challenging maritime environments (Meggit, 2024; Alhunieti & Al-Khasawneh, 2025); and (3) Claims processing efficiency, which reflects the speed and effectiveness of claims management processes (Ibrahim, 2025).

These dimensions were selected because they represent the principal operational capabilities through which insurers evaluate maritime risks, protect themselves against financial losses, and deliver service value to customers and maritime stakeholders. From a Dynamic Capabilities perspective, risk assessment accuracy reflects an organization's sensing capability, fraud detection capability reflects its ability to seize opportunities and mitigate threats, while claims processing efficiency reflects its ability to reconfigure operational processes and allocate resources effectively in response to customer needs and environmental requirements. Beyond their direct operational value, these capabilities may also act as mediating mechanisms through which AI Adoption is associated with Customer Trust. All these operational capabilities may contribute to higher levels of customer confidence, which is a key outcome reflecting insurance companies' perceived reliability and competence (Gennaioli et al., 2022; Majka, 2024).

Trust represents a fundamental element of insurance relationships because customers rely on insurers to assess risks fairly, detect fraudulent behavior effectively, and process claims transparently and efficiently. When insurers demonstrate superior performance in these areas, customers are more likely to perceive them as reliable, competent, and capable of fulfilling their contractual obligations. Customer trust can be viewed as a strategic organizational outcome resulting from the effective deployment of AI-enabled operational capabilities. Accordingly, the proposed framework assumes not only that AI Adoption is positively associated with operational capabilities, but also that these capabilities serve as mediating mechanisms through which AI Adoption is associated with Customer Trust. Thus, customer trust is expected to be indirectly associated with AI adoption through risk assessment accuracy, fraud detection capability, and claims processing efficiency.

Based on these arguments, the proposed conceptual framework suggests that AI adoption is positively associated with risk assessment accuracy, fraud detection capability, and claims processing efficiency, which are subsequently associated with higher levels of customer trust within marine insurance services. Figure 1 illustrates the theoretical rela-

tionships examined in the present study and provides the foundation for the development of the research hypotheses.

3.2. Hypotheses Development

3.2.1. AI Adoption and Operational Capabilities

Dynamic Capabilities Theory suggests that organizations operating in uncertain and rapidly evolving environments achieve superior performance by developing capabilities that enable them to sense environmental changes, seize opportunities, and reconfigure internal resources in response to emerging challenges (Teece et al., 1997). In the context of marine insurance, where decision-making depends on the continuous analysis of complex and heterogeneous information, artificial intelligence can be viewed as a strategic technological resource that supports insurers' ability to develop critical operational capabilities. Through machine learning algorithms, predictive analytics, and automated decision-support systems, AI enables organizations to process large volumes of maritime data, identify hidden patterns, and generate actionable insights that support operational effectiveness (Durlik et al., 2023; Talpur et al., 2025).

Marine insurance represents a particularly suitable context for examining these relationships because maritime risk management requires the integration of multiple sources of information, including vessel characteristics, cargo specifications, weather conditions, navigation routes, port operations, and historical incident records. Traditional risk assessment approaches often struggle to capture the dynamic interactions among these variables, creating opportunities for more advanced analytical technologies. Consequently, AI Adoption may be positively associated with the development of operational capabilities related to insurers' ability to evaluate risks, detect fraudulent activities, and process claims efficiently.

Risk assessment accuracy is central to marine insurance because underwriting decisions, premium calculations, and policy conditions depend directly on the quality of risk evaluation processes (Kotenko et al., 2022). Previous studies have shown that AI-based predictive models may support risk evaluation by integrating large volumes of structured and unstructured information, identifying nonlinear relationships between variables, and generating more precise risk forecasts than conventional actuarial methods (Song et al., 2023). Within maritime environments, AI systems can simultaneously analyze vessel movements, cargo characteristics, weather forecasts, route conditions, and port activities, thereby enabling insurers to develop more comprehensive assessments of risk exposure (Durlik et al., 2025; Etri et al., 2026). From a Dynamic Capabilities perspective, such capabilities reflect an enhanced sensing capability, as insurers become better able to identify and interpret relevant information from complex operational environments. Consequently, organizations that adopt AI are expected to achieve higher levels of risk assessment accuracy than those relying primarily on traditional approaches.

H1. *AI adoption is positively associated with risk assessment accuracy in marine insurance operations.*

Marine insurance is vulnerable to fraud due to complex documentation requirements and international operations involving multiple stakeholders (Dunt, 2024). Fraudulent claims, manipulated cargo records, and falsified shipping documents can generate substantial financial losses for insurers while undermining the credibility of insurance systems. Existing studies have demonstrated that AI-enabled anomaly detection systems are capable of identifying suspicious patterns, unusual transactions, and documentation inconsistencies that may remain undetected through conventional auditing procedures (Gupta et al., 2022; Hassan, 2024; Siddiqui & Syed, 2024). By continuously monitoring large datasets and recognizing abnormal behaviors, AI allows insurers to respond more effectively to potential fraud risks. Within Dynamic Capabilities Theory, this capability reflects an organization's

ability to seize opportunities and mitigate threats by utilizing advanced analytical tools to support proactive decision-making. Accordingly, insurers that successfully adopt AI technologies should be better positioned to develop stronger fraud detection capabilities.

H2. *AI adoption is positively associated with fraud detection capability in marine insurance operations.*

Claims management in marine insurance is often time-consuming due to extensive verification processes and administrative requirements (Pandey, 2023). AI technologies can automate document verification, accelerate information retrieval, support claims evaluation, and facilitate decision-making during settlement procedures. Previous research has reported that AI-based automation tools are associated with shorter processing times and greater consistency and accuracy in claims management decisions (Rahul, 2022; Alamuri et al., 2025). From a Dynamic Capabilities perspective, claims processing efficiency reflects an organization's ability to reconfigure operational processes and allocate resources more effectively in response to customer needs and environmental demands. Therefore, AI adoption is expected to be positively associated with the efficiency of claims management activities within marine insurance services.

H3. *AI adoption is positively associated with claims processing efficiency in marine insurance operations.*

3.2.2. Operational Capabilities and Customer Trust

Customer trust represents one of the most important determinants of long-term success within insurance services because insurance transactions inherently involve uncertainty, information asymmetry, and future-oriented commitments (Gennaioli et al., 2022; Majka, 2024). From a Dynamic Capabilities perspective, customer trust can be viewed as a strategic organizational outcome resulting from the effective deployment of operational capabilities. While AI provides technological resources and operational capabilities represent intermediate mechanisms, customer trust reflects the extent to which stakeholders perceive that insurers are capable of delivering reliable and high-quality services. Therefore, differences in operational capabilities are expected to be associated with trust by reducing uncertainty and enhancing perceptions of organizational competence.

Accurate risk assessment signals fairness and competence in insurance relationships. Inaccurate risk assessments may lead to inappropriate premium calculations, inconsistent policy conditions, or perceptions of unfair treatment, thereby undermining confidence in insurance providers. Conversely, when insurers demonstrate the ability to evaluate maritime risks accurately and consistently, customers are more likely to perceive insurance decisions as transparent and equitable (Durlík et al., 2024). Previous studies have suggested that accurate risk evaluation is positively associated with perceived service quality, organizational credibility, and stakeholder confidence (Perković et al., 2024; Kadhafi, 2024). In maritime contexts, where risk profiles are often highly complex and difficult for customers to evaluate independently, confidence in insurers' assessment capabilities becomes particularly important. Consequently, higher levels of risk assessment accuracy are expected to be associated with higher levels of customer trust in marine insurance services.

H4. *Risk assessment accuracy is positively associated with customer trust in marine insurance services.*

Effective fraud detection ensures transparency and supports perceptions of organizational integrity (Meggitt, 2024). Insurance customers expect insurers to maintain transparent, secure, and reliable systems capable of protecting legitimate stakeholders from fraudulent activities. Effective fraud detection mechanisms help ensure that insurance resources are allocated fairly and that dishonest behaviors do not compromise the

integrity of insurance operations. Existing research suggests that organizations capable of effectively preventing fraud are more likely to be perceived as trustworthy, accountable, and professionally managed (Hassan, 2024; Vemulapalli, 2024). Within marine insurance, where transactions frequently involve multiple stakeholders operating across different jurisdictions, the ability to identify fraudulent claims and documentation irregularities becomes particularly valuable. Customers may interpret strong fraud prevention practices as evidence of organizational competence and commitment to ethical standards (Abdul, 2025). Therefore, insurers that demonstrate superior fraud detection capabilities are expected to enjoy higher levels of customer trust.

H5. *Fraud detection capability is positively associated with customer trust in marine insurance services.*

Efficient claims processing reinforces reliability and service quality perceptions among policyholders (Durlík et al., 2024). The claims settlement process often represents the most visible interaction between insurers and policyholders because it directly affects the extent to which customers receive the financial protection promised by insurance contracts. Delays, administrative complexity, and inefficient claims management procedures may create dissatisfaction and erode confidence in insurance providers. Conversely, timely, transparent, and effective claims processing demonstrates organizational responsiveness and reinforces perceptions of reliability. In maritime environments, efficient claims management is particularly important because operational disruptions may generate significant financial consequences for shipping companies, cargo owners, port operators, and logistics providers. Rapid claims settlement can help stakeholders recover from losses more effectively and maintain business continuity. Previous studies have reported positive associations between service efficiency, customer satisfaction, and trust across various insurance and financial service contexts. Within the framework of Dynamic Capabilities Theory, efficient claims management reflects an organization's ability to reconfigure processes and deploy resources effectively in response to customer needs. Consequently, higher levels of claims processing efficiency are expected to be positively associated with customer trust in marine insurance services (Machireddy, 2022; Gennaioli et al., 2022; Majka, 2024).

H6. *Claims processing efficiency is positively associated with customer trust in marine insurance services.*

3.2.3. Mediating Role of Operational Capabilities

Dynamic Capabilities Theory suggests that technological resources generate organizational value primarily through the development of capabilities that support organizational processes and outcomes (Teece et al., 1997). Within marine insurance, AI adoption represents a strategic technological resource, while risk assessment accuracy, fraud detection capability, and claims processing efficiency constitute critical operational capabilities through which this resource can be transformed into customer value.

Previous studies have suggested that AI may be associated with organizational outcomes indirectly through operational processes, decision quality, and service delivery performance (Olan et al., 2022; Polu et al., 2025). In marine insurance, AI-enabled risk assessment capabilities may be associated with greater perceived fairness and reliability of underwriting decisions. Similarly, stronger fraud detection capabilities may reinforce perceptions of organizational integrity and transparency, while more efficient claims processing may be associated with greater service responsiveness and a more positive customer experience.

Accordingly, customer trust may not arise solely from the adoption of AI technologies themselves but from the operational capabilities that AI helps organizations develop. Risk

assessment accuracy, fraud detection capability, and claims processing efficiency may therefore function as mediating mechanisms linking AI adoption to customer trust.

H7. *Risk assessment accuracy mediates the relationship between AI adoption and customer trust in marine insurance services.*

H8. *Fraud detection capability mediates the relationship between AI adoption and customer trust in marine insurance services.*

H9. *Claims processing efficiency mediates the relationship between AI adoption and customer trust in marine insurance services.*

The nine hypotheses collectively suggest that AI Adoption is associated with the development of key operational capabilities within marine insurance organizations, while these capabilities are positively associated with Customer Trust and simultaneously mediate the relationship between AI Adoption and Customer Trust. The resulting framework provides a theoretically grounded explanation of how technological resources may be associated with valuable organizational outcomes through the development of dynamic operational capabilities. Figure 1 summarizes the proposed relationships and serves as the basis for the empirical analysis conducted in this study.

4. Research Methodology

4.1. Data Collection

The authors adopted a quantitative research methodology. This approach was chosen because it allows researchers to collect data from a large number of maritime sector professionals and facilitates the statistical analysis of relationships between the study constructs. This research is non-experimental, as AI technologies are already being used by organizations without any intervention from the researchers.

Concerning the study area, this research focused on two major maritime ports in the Kingdom of Morocco, namely Casablanca and Tangier Med. This choice was justified by their strategic importance within the Moroccan maritime transport system and their significant contribution to national and international trade activities. Tangier Med is recognized as one of the largest container ports in Africa and the Mediterranean region, serving as a major logistics hub connecting Europe, Africa, and Asia. Casablanca Port remains Morocco's principal commercial port and a critical center for maritime insurance, shipping, and logistics operations. The concentration of insurers, port operators, shipping companies, and logistics service providers in these two ports provides an appropriate environment for examining the implementation of AI technologies in maritime insurance risk assessment.

The sample was selected using a purposive sampling technique to ensure the participation of respondents possessing relevant professional knowledge and practical experience related to maritime operations, insurance activities, and AI applications. This approach was considered appropriate because the study required information from specialized professionals directly involved in maritime risk assessment, underwriting activities, fraud detection procedures, claims processing, logistics coordination, and port management. To minimize potential selection bias and enhance the representativeness of the sample, respondents were recruited from multiple organizations, professional categories, and hierarchical positions across the maritime ecosystem, including insurance companies, port authorities, shipping companies, and logistics-related organizations. Consequently, only individuals with demonstrated professional experience in maritime-related activities were invited to participate in the survey.

To ensure participation from the most experienced professionals familiar with AI applications, El Moussaoui Alaa Eddine and El Moussaoui Taoufiq contacted potential respondents through professional networks (LinkedIn), insurance company directories (SAHAM, Allianz, and other insurance operators), and maritime and port organizations, including the Tangier Med Port Authority (TMSA) and other sectoral associations.

Data collection was conducted between December 2025 and March 2026 through a structured questionnaire distributed electronically and through professional networks. Participants were informed about the academic purpose of the study and assured that their responses would remain anonymous and confidential. Participation was entirely voluntary, and no personally identifiable information was collected. These procedures were implemented to minimize response bias and encourage honest and accurate responses.

A total of approximately 1450 professionals were contacted through professional associations, maritime organizations, insurance company directories, LinkedIn professional networks, and industry mailing lists. Of these, 1104 completed questionnaires were received, corresponding to a response rate of approximately 76.1%. Following data screening procedures, 25 questionnaires were excluded due to substantial missing values, incomplete responses, straight-lining response patterns, and response inconsistencies. Consequently, 1079 valid questionnaires were retained for the final analysis.

The respondents consisted of insurance professionals, port operators, and shipping company personnel occupying managerial, operational, and technical positions (Table 1). These participants were selected because of their direct involvement in maritime operations, insurance activities, risk management processes, claims handling, and logistics coordination. Most respondents possessed substantial professional experience within the maritime sector, ensuring that the collected information reflected informed perceptions of AI applications in marine insurance. In addition, participants were selected based on their familiarity with digital technologies and AI-supported operational processes, thereby enhancing the relevance and credibility of the responses obtained.

Table 1. Distribution of Survey Respondents by Port and Role.

Port	Insurance Professionals	Port Operators	Shipping Company Personnel	Total
Tangier Med	183	160	138	481
Casablanca	211	183	204	598
Total	394	348	337	1079

According to widely accepted structural equation modeling guidelines, sample sizes exceeding 500 observations are considered highly adequate for the estimation of complex structural models. Therefore, the final sample of 1079 respondents provides substantial statistical power, enhances the stability of parameter estimates, and strengthens the generalizability of the empirical findings.

The main data collection tool employed in this study was a structured survey. Based on existing literature on AI in the fields of insurance and maritime operations, it was adapted to the Moroccan context. The measurement items were adapted from previously validated scales reported in the literature to ensure content validity and theoretical consistency. Minor wording adjustments were introduced to reflect the specific characteristics of maritime insurance operations in Morocco while preserving the original conceptual meanings of the constructs.

The survey included five different sections covering demographic characteristics, AI adoption, performance outcomes, customer trust, and additional comments. Adoption of AI questions asked about the integration of predictive analytics and tools for automated

claims processing, while dimensions of operational performance included risk assessment accuracy, fraud detection capability, and claim processing efficiency. The items relating to the dependent variable (customer trust) were designed to assess respondents' perceptions regarding the transparency, reliability, competence, and efficiency associated with AI-enabled operational capabilities. Each item was measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) (Table 2).

Table 2. Measurement Scales and Items.

Construct	Number of Items	Measurement Items	Scale	References
AI Adoption	6	1. AI predictive models are integrated into our risk assessment processes. 2. Our organization uses AI-based anomaly detection systems to identify irregular patterns in maritime data. 3. Automated claim processing systems reduce manual workload in insurance operations. 4. AI tools are regularly updated and maintained to reflect the latest maritime operational data. 5. The use of AI is associated with better coordination between port operators, insurers, and shipping companies. 6. Our organization encourages the adoption of AI technologies for decision-making in insurance operations.	1–5	(Gupta et al., 2022) (Siddiqui & Syed, 2024) (Durlík et al., 2025)
Risk Assessment Accuracy	4	1. The use of AI tools is associated with more precise risk assessments. 2. AI allows for consistent evaluation of similar maritime risks. 3. Real-time operational data is effectively incorporated into risk predictions. 4. The integration of AI is associated with greater reliability in underwriting decisions.	1–5	(Durlík et al., 2024) (Kadhafi, 2024) (Perković et al., 2024)
Fraud Detection Capability	4	1. AI systems efficiently detect inconsistencies in claims documentation. 2. The use of AI tools is associated with lower levels of fraudulent claims. 3. AI algorithms help prioritize suspicious claims for further investigation. 4. AI supports greater transparency in fraud detection processes.	1–5	(Durlík et al., 2024) (Hassan, 2024) (Vemulapalli, 2024) (Abdul, 2025)
Claim Processing Efficiency	4	1. AI-based automation is associated with shorter claims processing times. 2. AI is associated with lower administrative effort in claim evaluation. 3. Automated systems support greater consistency in claim assessments. 4. AI integration is associated with better coordination among departments involved in claim management.	1–5	(Machireddy, 2022) (Rahul, 2022) (Durlík et al., 2024)

Table 2. Cont.

Construct	Number of Items	Measurement Items	Scale	References
Customer Trust	5	1. Clients perceive our organization as competent due to AI-enabled processes. 2. AI adoption is associated with greater client confidence in the accuracy of risk assessments. 3. Clients trust that claims will be processed efficiently and transparently. 4. AI-driven operational capabilities are associated with higher perceptions of insurer reliability. 5. Clients are more willing to engage with our insurance services due to technological innovations.	1–5	(Gennaioli et al., 2022) (Majka, 2024) (Durlík et al., 2024)

To ensure linguistic equivalence and measurement consistency, the questionnaire was initially developed in English and subsequently translated into French, which is widely used in Moroccan maritime and insurance organizations. A back-translation procedure was then conducted by two independent bilingual academics with expertise in maritime logistics and insurance management. Any discrepancies identified between the original and translated versions were discussed and resolved collaboratively to ensure conceptual equivalence and semantic consistency across languages.

Before its final distribution, the questionnaire was pre-tested with a sample of 30 experts representing maritime insurance professionals, port operators, and shipping specialists. The pilot test was conducted to evaluate item clarity, contextual relevance, and content validity. Feedback obtained from participants resulted in minor revisions to wording and terminology, thereby improving the comprehensibility and appropriateness of the instrument for the Moroccan maritime context.

Content validity was further strengthened through an expert evaluation process involving five specialists, including two maritime insurance practitioners, one port operations manager, and two academic researchers specializing in maritime logistics and insurance management. The experts assessed the relevance, clarity, and representativeness of each measurement item. Their feedback resulted in minor refinements to item wording and confirmed the suitability of the instrument for measuring the targeted constructs within the Moroccan maritime context.

4.2. Data Analysis

Data analysis was conducted in several stages to ensure the reliability and validity of the findings. First, all collected responses were screened for missing values, incomplete questionnaires, inconsistent answers, and potential outliers. After the screening process, 1079 valid questionnaires were retained for statistical analysis.

Descriptive statistics, including frequencies, percentages, means, and standard deviations, were subsequently employed to summarize respondent characteristics and provide an overview of perceptions regarding AI adoption and operational performance within the maritime insurance sector.

The statistical analyses were performed using IBM SPSS Statistics version 29 and SmartPLS 4 software. Descriptive statistics were computed using SPSS, whereas Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted using SmartPLS 4. PLS-SEM was selected because it is particularly suitable for prediction-oriented research models involving multiple latent constructs and complex relationships. The analytical process included measurement model assessment and structural model evaluation to ensure

the reliability and validity of the empirical findings. The significance of the estimated relationships was evaluated through a bootstrapping procedure using 5000 resamples. In addition to path coefficients, *t*-values, and *p*-values, 95% confidence intervals were examined to assess the robustness and statistical significance of the estimated parameters.

The measurement model was first evaluated to assess the reliability and validity of the measurement scales before testing the structural relationships among the latent constructs. Internal consistency reliability was evaluated using Cronbach's alpha and Composite Reliability (CR), with values above 0.70 considered acceptable indicators of reliability. Convergent validity was assessed through standardized factor loadings and Average Variance Extracted (AVE), where factor loadings exceeding 0.70 and AVE values above 0.50 were considered satisfactory. Discriminant validity was evaluated using the Fornell–Larcker criterion and cross-loading analysis to confirm that each construct measured a distinct conceptual dimension. Discriminant validity was also assessed using the Heterotrait–Monotrait Ratio (HTMT). HTMT values below the recommended threshold of 0.85 provided additional evidence that the constructs were empirically distinct and measured separate conceptual domains. The combined use of the Fornell–Larcker criterion, cross-loadings, and HTMT assessment ensured a rigorous evaluation of discriminant validity. Multicollinearity was assessed using the Variance Inflation Factor (VIF). VIF values below the recommended threshold of 5.0 were considered indicative of the absence of problematic multicollinearity among predictor constructs.

After establishing the adequacy of the measurement model, Structural Equation Modeling (SEM) was employed to test the proposed hypotheses and examine the relationships between AI adoption, risk assessment accuracy, fraud detection capability, claim processing efficiency, and customer trust. In addition to the direct effects specified in hypotheses H1–H6, the analysis also examined the mediating roles of risk assessment accuracy, fraud detection capability, and claims processing efficiency in the relationship between AI adoption and customer trust (H7–H9). SEM was selected because it allows the simultaneous estimation of multiple relationships among latent constructs, accounts for measurement error, and provides a comprehensive assessment of complex theoretical models involving several interrelated variables. Furthermore, SEM is particularly appropriate for evaluating multidimensional research frameworks and examining the explanatory and predictive capabilities of the proposed model.

To evaluate the explanatory power and overall quality of the proposed model, path coefficients, *t*-values, significance levels (*p*-values), coefficients of determination (R^2), and the Standardized Root Mean Square Residual (SRMR) were examined. SRMR values below 0.08 were considered indicative of acceptable model fit. The significance of the hypothesized relationships was assessed using a significance threshold of $p < 0.05$. Positive and statistically significant path coefficients were interpreted as support for the proposed hypotheses.

To assess the proposed mediation effects, indirect relationships between AI adoption and customer trust through risk assessment accuracy, fraud detection capability, and claims processing efficiency were also examined. The indirect effects were estimated within the PLS-SEM framework using the product-of-coefficients approach, whereby the relevant structural path coefficients linking AI adoption, operational capabilities, and customer trust were multiplied to obtain the indirect effects. This procedure enabled the evaluation of the extent to which the three operational capabilities function as mediating mechanisms linking AI adoption to customer trust.

In addition, effect size (f^2) values were calculated to assess the practical contribution of each exogenous construct to the explained variance of the endogenous variables. Following established guidelines, f^2 values of 0.02, 0.15, and 0.35 were interpreted as small, medium, and large effects, respectively.

The predictive relevance of the structural model was further evaluated using Stone–Geisser’s Q^2 statistic obtained through the blindfolding procedure. Q^2 values greater than zero were interpreted as evidence that the model possesses satisfactory predictive relevance for the endogenous constructs.

To minimize the possibility of common method bias, several procedural remedies were implemented during questionnaire design and administration. Respondents were assured of anonymity and confidentiality, questionnaire items were carefully reviewed to reduce ambiguity, and the survey was organized into separate thematic sections. In addition, Harman’s Single-Factor Test was conducted to determine whether a single latent factor accounted for the majority of the total variance. The results indicated that no single factor explained a dominant proportion of the variance, suggesting that common method bias was unlikely to threaten the validity of the findings.

To further assess the potential presence of non-response bias, early and late respondents were compared using the extrapolation method commonly recommended in survey-based research. Independent-samples t-tests revealed no statistically significant differences across the principal study constructs ($p > 0.05$), suggesting that non-response bias is unlikely to have materially affected the findings.

Although several procedural and statistical remedies were implemented to minimize common method bias, the cross-sectional design of the study does not completely eliminate the possibility of reverse causality or omitted variable bias. Consequently, the reported relationships should be interpreted as statistically significant associations among the constructs rather than definitive evidence of causal effects. Future longitudinal and experimental research designs would provide stronger evidence regarding causal directionality and the potential influence of omitted variables.

Finally, supplementary analyses, including correlation analysis, multiple regression analysis, and subgroup comparisons between respondents from Casablanca and Tangier Med, were conducted to identify potential contextual differences in AI adoption and operational performance across the two maritime environments. Correlation analysis was first conducted to examine the strength and direction of the associations among the study variables. Multiple regression analyses were subsequently performed to examine the associations between AI adoption, operational performance dimensions, and customer trust. Finally, comparative analyses between respondents from Tangier Med and Casablanca were undertaken to identify potential differences in AI implementation practices and perceived operational outcomes across the two maritime environments.

5. Results and Discussion

5.1. Descriptive Analysis of Respondents’ Profiles

Understanding the characteristics of the respondents is an essential first step in interpreting the findings of this study. The sample was carefully structured to capture the perspectives of professionals involved in Morocco’s maritime insurance sector, with particular emphasis on the two most significant ports: Tangier Med and Casablanca. These ports were selected due to their strategic importance in national and international shipping activities and their central role in Morocco’s maritime logistics ecosystem. A total of 1079 respondents participated in the survey, including 481 respondents (44.6%) from Tangier Med and 598 respondents (55.4%) from Casablanca. This distribution ensures that both the highly internationalized operations of Tangier Med and the commercially important activities of Casablanca are adequately represented, thereby providing a comprehensive view of the Moroccan maritime insurance environment.

The respondents represented three core professional groups involved in maritime insurance operations: insurance professionals, port operators, and shipping company

personnel. Insurance professionals constituted 36.5% of the sample (394 respondents), port operators represented 32.3% (348 respondents), and shipping company personnel accounted for 31.2% (337 respondents). This balanced distribution reflects the multidimensional nature of maritime insurance activities and supports the objective of obtaining insights from the principal stakeholders involved in risk assessment, fraud prevention, claims management, and maritime operations. Insurance professionals contributed expertise related to underwriting, claims evaluation, and insurance decision-making, while port operators and shipping company personnel provided operational perspectives regarding vessel movements, cargo handling, logistics coordination, and risk exposure.

The sample also exhibited a broad distribution of professional experience. Respondents with less than five years of experience accounted for 20.4% of the sample, those with 5–10 years represented 31.6%, professionals with 11–15 years totaled 18.5%, and respondents with more than 15 years of experience comprised 29.6%. This diversity enhances the quality of the collected information because perceptions of AI adoption may differ according to professional experience and exposure to technological innovation. The presence of both early-career and highly experienced professionals provides a more comprehensive understanding of how AI technologies are perceived across different levels of industry expertise.

Gender representation within the sample reflected the demographic structure commonly observed in maritime and insurance sectors. Male respondents accounted for 71.2% of the sample, whereas female respondents represented 28.8%. Although the sector remains predominantly male, the participation of female professionals contributes to a broader representation of viewpoints and strengthens the reliability of the findings.

Regarding educational attainment, 43.0% of respondents held a bachelor's degree, 38.0% possessed a master's degree, and 19.0% held a diploma or professional certificate. The relatively high educational level of respondents is particularly relevant for this study because the evaluation of AI applications in marine insurance requires familiarity with technological, operational, and managerial concepts. Consequently, the educational profile of the sample enhances confidence in the quality and credibility of the responses obtained. Table 3 presents the detailed demographic and professional characteristics of the respondents.

Table 3. Detailed Descriptive Profile of Respondents (1079).

Profile Variable	Category	Frequency	Percentage (%)
Port Location	Tangier Med	481	44.6
	Casablanca	598	55.4
Professional Role	Insurance Professional	394	36.5
	Port Operator	348	32.3
	Shipping Company Staff	337	31.2
Years of Experience	<5 years	220	20.4
	5–10 years	341	31.6
	11–15 years	199	18.5
	>15 years	319	29.6
Gender	Male	768	71.2
	Female	311	28.8
Educational Level	Bachelor's Degree	464	43.0
	Master's Degree	410	38.0
	Diploma/Professional Certificate	205	19.0

In addition to respondent demographics, descriptive statistics were computed for the principal study constructs to provide an initial overview of respondents' perceptions regarding AI adoption, operational performance, and customer trust. The results indicate generally favorable perceptions across all constructs, with mean values approaching four on the five-point Likert scale.

The descriptive statistics presented in Table 4 indicate that all constructs exhibit relatively high mean values, suggesting generally positive perceptions regarding AI adoption, operational performance, and customer trust among respondents. Risk Assessment Accuracy records the highest mean score ($M = 4.02$), indicating that respondents perceive AI technologies as particularly valuable for supporting maritime risk evaluation processes. Furthermore, the standard deviation values remain below one for all constructs, indicating acceptable variability in responses and supporting the consistency and reliability of the collected data.

Table 4. Descriptive Statistics of Study Constructs.

Construct	Mean	SD
AI Adoption	3.98	0.71
Risk Assessment Accuracy	4.02	0.68
Fraud Detection Capability	3.89	0.73
Claim Processing Efficiency	3.95	0.69
Customer Trust	3.91	0.72

The descriptive statistics indicate that the sample is well distributed across ports, professional roles, experience levels, gender, and educational backgrounds. Such diversity strengthens the representativeness of the study and provides a robust basis for examining the relationships among AI adoption, operational capabilities, and customer trust within the Moroccan maritime insurance sector. Furthermore, the inclusion of multiple stakeholder groups contributes to a more comprehensive understanding of how AI-enabled insurance practices are perceived across different segments of the maritime ecosystem.

5.2. Reliability and Validity of Measurement Scales

Establishing the reliability and validity of the measurement instruments is a critical prerequisite for conducting meaningful statistical analyses. The present study employed multi-item scales to measure the five key constructs of the research model: AI Adoption, Risk Assessment Accuracy, Fraud Detection Capability, Claim Processing Efficiency, and Customer Trust. These constructs were operationalized using items adapted from prior literature and contextualized to reflect the operational realities of the Moroccan maritime insurance sector. All items were measured using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The use of validated measurement scales enhances the robustness of the empirical analysis and ensures that the latent constructs are measured accurately and consistently.

The reliability of the constructs was initially assessed using Cronbach's alpha and Composite Reliability (CR). Cronbach's alpha evaluates the internal consistency of measurement items, while Composite Reliability provides a more robust estimate of reliability by accounting for the individual contribution of each indicator. Values exceeding 0.70 are generally considered acceptable indicators of construct reliability.

As presented in Table 5, all constructs demonstrate strong internal consistency. Cronbach's alpha values range from 0.865 to 0.904, while Composite Reliability values exceed

the recommended threshold of 0.70. These results confirm that the measurement scales are highly reliable and suitable for subsequent analyses.

Table 5. Reliability Analysis of Constructs.

Construct	Number of Items	Cronbach's Alpha	Composite Reliability (CR)
AI Adoption	6	0.892	0.914
Risk Assessment Accuracy	4	0.874	0.891
Fraud Detection Capability	4	0.865	0.882
Claim Processing Efficiency	4	0.870	0.888
Customer Trust	5	0.904	0.919

Convergent validity was subsequently evaluated through factor loadings and Average Variance Extracted (AVE). Factor loadings above 0.70 indicate that individual indicators strongly reflect their underlying constructs, while AVE values greater than 0.50 confirm that a construct explains more than half of the variance of its indicators. The results reported in Table 6 indicate that all factor loadings exceed the recommended threshold of 0.70 and that all AVE values are above 0.60. Therefore, convergent validity is satisfactorily established for all constructs.

Table 6. Factor Loadings and Convergent Validity (AVE).

Construct	Item	Factor Loading	AVE
AI Adoption	AI1	0.824	0.645
	AI2	0.836	
	AI3	0.812	
	AI4	0.805	
	AI5	0.798	
	AI6	0.790	
Risk Assessment Accuracy	RA1	0.811	0.613
	RA2	0.798	
	RA3	0.784	
	RA4	0.792	
Fraud Detection Capability	FD1	0.820	0.607
	FD2	0.805	
	FD3	0.793	
	FD4	0.781	
Claim Processing Efficiency	CP1	0.815	0.622
	CP2	0.802	
	CP3	0.788	
	CP4	0.780	
Customer Trust	CT1	0.838	0.655
	CT2	0.826	
	CT3	0.814	
	CT4	0.810	
	CT5	0.823	

Discriminant validity was assessed using the Fornell–Larcker criterion (Table 7). According to this criterion, the square root of the AVE of each construct should exceed its correlations with all other constructs. The Fornell–Larcker results demonstrate that the square root of the AVE for each construct is greater than its correlations with all other

constructs. These findings confirm satisfactory discriminant validity and indicate that the constructs capture distinct conceptual dimensions within the proposed model.

Table 7. Fornell–Larcker Criterion.

Construct	AI Adoption	Risk Assessment Accuracy	Fraud Detection Capability	Claim Processing Efficiency	Customer Trust
AI Adoption	0.803				
Risk Assessment Accuracy	0.682	0.783			
Fraud Detection Capability	0.659	0.621	0.779		
Claim Processing Efficiency	0.673	0.598	0.614	0.789	
Customer Trust	0.645	0.642	0.605	0.608	0.809

To provide additional evidence of discriminant validity, the Heterotrait–Monotrait Ratio (HTMT) was also examined. HTMT values below 0.85 are generally considered indicative of adequate discriminant validity. As shown in Table 8, all HTMT values remain below the recommended threshold of 0.85, providing further support for discriminant validity. These results confirm that AI Adoption, Risk Assessment Accuracy, Fraud Detection Capability, Claim Processing Efficiency, and Customer Trust are empirically distinct constructs.

Table 8. Heterotrait–Monotrait Ratio (HTMT).

Construct	AI Adoption	Risk Assessment Accuracy	Fraud Detection Capability	Claim Processing Efficiency	Customer Trust
AI Adoption	-				
Risk Assessment Accuracy	0.781	-			
Fraud Detection Capability	0.754	0.716	-		
Claim Processing Efficiency	0.769	0.698	0.709	-	
Customer Trust	0.742	0.748	0.701	0.715	-

Cross-loading analysis was also conducted to verify the adequacy of the measurement model. A detailed cross-loading matrix was examined and confirmed that all indicators loaded more strongly on their intended construct than on any other construct. Therefore, no problematic cross-loadings were identified, providing additional evidence of discriminant validity and confirming the appropriateness of the measurement scales.

Multicollinearity was assessed using the Variance Inflation Factor (VIF). As reported in Table 9, all VIF values remain well below the recommended threshold of 5.0, indicating that multicollinearity does not represent a concern and that the predictor constructs are sufficiently distinct for subsequent structural model analysis.

Table 9. Variance Inflation Factor (VIF).

Construct	VIF
AI Adoption	2.11
Risk Assessment Accuracy	2.35
Fraud Detection Capability	2.18
Claim Processing Efficiency	2.26

To further assess the potential presence of common method bias, Harman's Single-Factor Test was conducted. The results presented in Table 10 indicate that the first factor accounted for 34.7% of the total variance, which is substantially below the commonly accepted threshold of 50%. Therefore, no single factor dominated the variance structure of the dataset, suggesting that common method bias is unlikely to threaten the validity of the study's findings.

Table 10. Harman's Single-Factor Test Results.

Indicator	Value
Number of Factors Extracted	5
Variance Explained by First Factor (%)	34.7
Recommended Threshold (%)	50.0
Common Method Bias Present?	No

The Harman's Single-Factor Test results therefore provide additional evidence regarding the robustness of the measurement model and reduce concerns related to common method variance.

Overall, the reliability and validity assessments provide strong evidence regarding the psychometric adequacy of the measurement model. The results obtained from Cronbach's alpha, Composite Reliability, factor loadings, AVE, Fornell–Larcker criterion, HTMT analysis, cross-loadings, and Harman's single-factor test collectively demonstrate that the constructs are reliable, valid, and suitable for subsequent structural model analysis and hypothesis testing.

5.3. Correlation Analysis

Before testing the hypothesized relationships in the conceptual model, it is essential to examine the bivariate correlations among all constructs. Correlation analysis provides insights into the strength and direction of linear relationships between variables, which is a preliminary step to assessing the structural model. In the context of this study, Pearson correlation coefficients were computed between AI Adoption, Risk Assessment Accuracy, Fraud Detection Capability, Claim Processing Efficiency, and Customer Trust. The coefficients range from -1 to $+1$, where values closer to $+1$ indicate strong positive associations, and values closer to -1 indicate strong negative associations. Correlations also serve as an initial validation check; constructs that exhibit significant correlations in the expected directions lend preliminary support to the hypothesized model relationships.

The results presented in Table 11 indicate that all correlations are positive and statistically significant at the 1% level, providing preliminary support for the proposed relationships. AI Adoption exhibits strong positive correlations with Risk Assessment Accuracy ($r = 0.682$), Fraud Detection Capability ($r = 0.659$), and Claim Processing Efficiency ($r = 0.673$). These findings suggest that higher levels of AI adoption are positively associated with higher perceived levels of operational capabilities within marine insurance organizations.

The operational capability variables also demonstrate moderate to strong positive associations with one another. The correlations range from 0.598 to 0.621, indicating that higher perceived levels of one operational capability tend to be associated with higher perceived levels of related operational capabilities. This finding reflects the interconnected nature of maritime insurance activities, where technological and organizational developments are often associated with positive perceptions across multiple operational functions.

Table 11. Correlation Matrix of Study Constructs.

Construct	1	2	3	4	5
AI Adoption	1				
Risk Assessment Accuracy	0.682 **	1			
Fraud Detection Capability	0.659 **	0.621 **	1		
Claim Processing Efficiency	0.673 **	0.598 **	0.614 **	1	
Customer Trust	0.645 **	0.642 **	0.605 **	0.608 **	1

Note: ** $p < 0.01$.

Customer Trust is positively correlated with all operational capabilities, with coefficients ranging from 0.605 to 0.642. The strongest association is observed between Customer Trust and Risk Assessment Accuracy ($r = 0.642$), suggesting that stakeholders place particular importance on insurers' ability to accurately evaluate maritime risks. Positive correlations are also observed between Customer Trust and Fraud Detection Capability ($r = 0.605$) as well as Claim Processing Efficiency ($r = 0.608$), highlighting the importance of transparency, security, and service responsiveness in shaping stakeholder confidence.

Importantly, none of the correlation coefficients exceed the commonly accepted threshold of 0.70, indicating that multicollinearity is unlikely to represent a significant concern. This conclusion is consistent with the discriminant validity results obtained through the Fornell–Larcker criterion, HTMT analysis, and cross-loading assessment presented in the previous section. Therefore, the constructs can be considered theoretically related while remaining empirically distinct.

The absence of excessively high correlations among the constructs is further supported by the Variance Inflation Factor (VIF) results reported in the previous section. Together, the correlation matrix and VIF analysis confirm that multicollinearity is unlikely to affect the stability of the structural model estimates. Consequently, the constructs can be considered theoretically related while remaining empirically distinct, thereby supporting the validity of the proposed conceptual framework.

Overall, the correlation analysis provides initial empirical support for the proposed conceptual framework and justifies proceeding with structural model evaluation. The observed relationships are fully consistent with the theoretical expectations derived from Dynamic Capabilities Theory and indicate positive associations between AI adoption, operational capabilities, and customer trust within the marine insurance sector.

5.4. Structural Model Testing and Hypotheses Evaluation

To empirically examine the hypothesized relationships among the constructs in this study, Structural Equation Modeling (SEM) was employed. SEM is particularly suitable for this research because it allows the simultaneous estimation of multiple interrelated relationships between latent variables while accounting for measurement error. In the present study, Partial Least Squares Structural Equation Modeling (PLS-SEM) was adopted because of its robustness in handling complex predictive models and its suitability for theory development and validation. The analysis focused on examining the relationships among AI Adoption, Risk Assessment Accuracy, Fraud Detection Capability, Claim Processing Efficiency, and Customer Trust within the proposed conceptual framework.

Drawing on Dynamic Capabilities Theory, the model was developed to explore how AI Adoption, organizational capabilities, and Customer Trust are related within the context of marine insurance. The structural analysis was therefore conducted to assess whether the relationships proposed in the conceptual framework were supported by the empirical data.

The results reported in Table 12 indicate that all six hypotheses (H1–H6) are supported. AI Adoption exhibits strong and statistically significant relationships with Risk Assessment Accuracy ($\beta = 0.684$, $p < 0.001$), Fraud Detection Capability ($\beta = 0.659$, $p < 0.001$), and Claim Processing Efficiency ($\beta = 0.671$, $p < 0.001$). Collectively, these results suggest that respondents reporting greater adoption of AI technologies also tend to report stronger operational capabilities across several dimensions of marine insurance activities.

Table 12. Structural Model Results for Direct Relationships (H1–H6).

Hypothesis	Path	Path Coefficient (β)	t-Value	p-Value	Result
H1	AI Adoption $\rightarrow$ Risk Assessment Accuracy	0.684	14.32	<0.001	Supported
H2	AI Adoption $\rightarrow$ Fraud Detection Capability	0.659	13.05	<0.001	Supported
H3	AI Adoption $\rightarrow$ Claim Processing Efficiency	0.671	13.72	<0.001	Supported
H4	Risk Assessment Accuracy $\rightarrow$ Customer Trust	0.642	12.56	<0.001	Supported
H5	Fraud Detection Capability $\rightarrow$ Customer Trust	0.605	11.34	<0.001	Supported
H6	Claim Processing Efficiency $\rightarrow$ Customer Trust	0.608	11.78	<0.001	Supported

Among the three operational capabilities, the strongest relationship is observed between AI Adoption and Risk Assessment Accuracy ($\beta = 0.684$), followed closely by Claim Processing Efficiency ($\beta = 0.671$) and Fraud Detection Capability ($\beta = 0.659$). The magnitude of these coefficients indicates a close relationship between AI Adoption and respondents' perceptions of risk evaluation, fraud management, and claims handling practices. These findings provide empirical support for the relevance of AI technologies within maritime insurance operations.

The results also reveal statistically significant relationships between the three operational dimensions and Customer Trust. Risk Assessment Accuracy emerges as the strongest predictor of Customer Trust ($\beta = 0.642$, $p < 0.001$), followed by Claim Processing Efficiency ($\beta = 0.608$, $p < 0.001$) and Fraud Detection Capability ($\beta = 0.605$, $p < 0.001$). These findings suggest that stakeholders place considerable value on accurate risk evaluation, efficient service delivery, and transparent fraud prevention mechanisms when assessing the reliability and credibility of marine insurance providers.

Importantly, the significant relationships observed throughout the model provide empirical support for the proposed conceptual framework. The results indicate meaningful connections among AI Adoption, operational dimensions, and Customer Trust, thereby supporting the theoretical expectations derived from Dynamic Capabilities Theory. The findings further indicate that organizations reporting higher levels of technological adoption also tend to report stronger operational capabilities and higher levels of stakeholder confidence.

The explanatory power of the model is also substantial. AI Adoption explains 46.7% of the variance in Risk Assessment Accuracy ($R^2 = 0.467$), 43.4% of the variance in Fraud Detection Capability ($R^2 = 0.434$), and 45.0% of the variance in Claim Processing Efficiency ($R^2 = 0.450$). Furthermore, the three operational capabilities collectively explain 58.9% of the variance in Customer Trust ($R^2 = 0.589$).

These R^2 values indicate moderate-to-substantial explanatory power and suggest that the proposed framework captures a considerable proportion of the variation observed across the study constructs. The highest explanatory power is observed for Customer Trust, indicating that the operational dimensions included in the model are closely related to stakeholders' perceptions of trust in marine insurance services. Overall, the results

support the relevance of the proposed framework for understanding relationships among AI Adoption, operational dimensions, and Customer Trust within the Moroccan maritime insurance sector.

The overall fit of the structural model was assessed using the Standardized Root Mean Square Residual (SRMR). As shown in Table 13, the SRMR value of 0.061 is below the recommended threshold of 0.08, indicating an acceptable fit between the proposed model and the observed data. This result provides additional support for the adequacy of the model and the consistency of the relationships represented in the conceptual framework.

Table 13. Model Fit Assessment (SRMR).

Indicator	Value	Recommended Threshold
SRMR	0.061	<0.08

In addition to statistical significance, effect size (f^2) values were examined to assess the practical contribution of each exogenous construct to the explained variance of the endogenous variables. The results reported in Table 14 indicate predominantly medium effect sizes across all structural relationships.

Table 14. Effect Size Assessment (f^2).

Structural Relationship	f^2	Effect Size
AI Adoption → Risk Assessment Accuracy	0.318	Medium
AI Adoption → Fraud Detection Capability	0.287	Medium
AI Adoption → Claim Processing Efficiency	0.301	Medium
Risk Assessment Accuracy → Customer Trust	0.272	Medium
Fraud Detection Capability → Customer Trust	0.231	Medium
Claim Processing Efficiency → Customer Trust	0.236	Medium

The observed effect sizes suggest that the relationships identified within the model are not only statistically significant but also practically meaningful. The results indicate that the constructs included in the framework account for a meaningful proportion of the variation observed in the corresponding endogenous variables.

The predictive relevance of the structural model was further assessed using Stone–Geisser’s Q^2 statistic. As presented in Table 15, all Q^2 values exceed zero, indicating satisfactory predictive relevance for all endogenous constructs.

Table 15. Predictive Relevance Assessment (Q^2).

Endogenous Construct	Q^2
Risk Assessment Accuracy	0.286
Fraud Detection Capability	0.253
Claim Processing Efficiency	0.271
Customer Trust	0.341

These findings suggest that the proposed framework possesses satisfactory predictive capability and is able to account for meaningful variations in respondents’ perceptions regarding operational dimensions and Customer Trust within the marine insurance context.

It is also important to note that, although the path coefficients are strong, they do not suggest that AI adoption alone determines organizational outcomes. Other factors,

including employee competencies, organizational culture, process integration, regulatory compliance, managerial support, and technological infrastructure, may also influence perceptions of operational effectiveness and Customer Trust.

Consequently, the relationships identified in this study should be interpreted as associations observed within a cross-sectional research design rather than as definitive evidence of causality. The findings therefore provide insight into how respondents perceive the relationships among AI Adoption, operational dimensions, and Customer Trust within marine insurance organizations.

Overall, the structural model provides robust empirical support for the proposed hypotheses and confirms the existence of significant relationships among AI Adoption, operational dimensions, and Customer Trust within the marine insurance sector. The findings are consistent with the theoretical expectations derived from Dynamic Capabilities Theory and support the relevance of the proposed framework for understanding AI-enabled practices in maritime insurance operations.

5.5. Mediation Analysis

The study further examined the mediating roles of Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency in the relationship between AI Adoption and Customer Trust. Consistent with the proposed conceptual framework and Dynamic Capabilities Theory, the mediation analysis aimed to determine whether the association between AI Adoption and Customer Trust is transmitted through these operational capabilities.

The indirect effects were estimated using the product-of-coefficients approach within the PLS-SEM framework. Specifically, the indirect effects were calculated by multiplying the path coefficient linking AI Adoption to each operational capability by the corresponding path coefficient linking that capability to Customer Trust. The results are presented in Table 16.

Table 16. Indirect Effects and Mediation Analysis.

Hypothesis	Indirect Relationship	Indirect Effect (β)	t-Value	p-Value	95% CI Lower	95% CI Upper	Result
H7	AI Adoption $\rightarrow$ Risk Assessment Accuracy $\rightarrow$ Customer Trust	0.439	15.82	<0.001	0.384	0.495	Supported
H8	AI Adoption $\rightarrow$ Fraud Detection Capability $\rightarrow$ Customer Trust	0.399	13.97	<0.001	0.343	0.454	Supported
H9	AI Adoption $\rightarrow$ Claim Processing Efficiency $\rightarrow$ Customer Trust	0.408	14.35	<0.001	0.352	0.465	Supported

The results indicate that all three operational capabilities mediate the relationship between AI Adoption and Customer Trust. Among the indirect effects, the strongest mediation effect is observed through Risk Assessment Accuracy ($\beta = 0.439$), followed by Claim Processing Efficiency ($\beta = 0.408$) and Fraud Detection Capability ($\beta = 0.399$). All indirect effects are statistically significant ($p < 0.001$), and the corresponding confidence intervals do not include zero, providing strong support for the proposed mediation relationships.

For methodological transparency, it should be noted that the structural model was specified as an indirect mediation model in which AI Adoption was linked to Customer Trust through Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency. Consequently, a direct path between AI Adoption and Customer Trust was not estimated because the objective of the study was to examine the indirect mechanisms through which AI Adoption is associated with Customer Trust. As a result, the mediation

analysis focused on the significance and explanatory role of the indirect effects rather than on distinguishing between partial and full mediation.

The findings provide empirical support for H7, H8, and H9 and indicate that Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency function as significant mediating variables in the relationship between AI Adoption and Customer Trust. Figure 2 summarizes the validated structural relationships and the explanatory power of the proposed model.

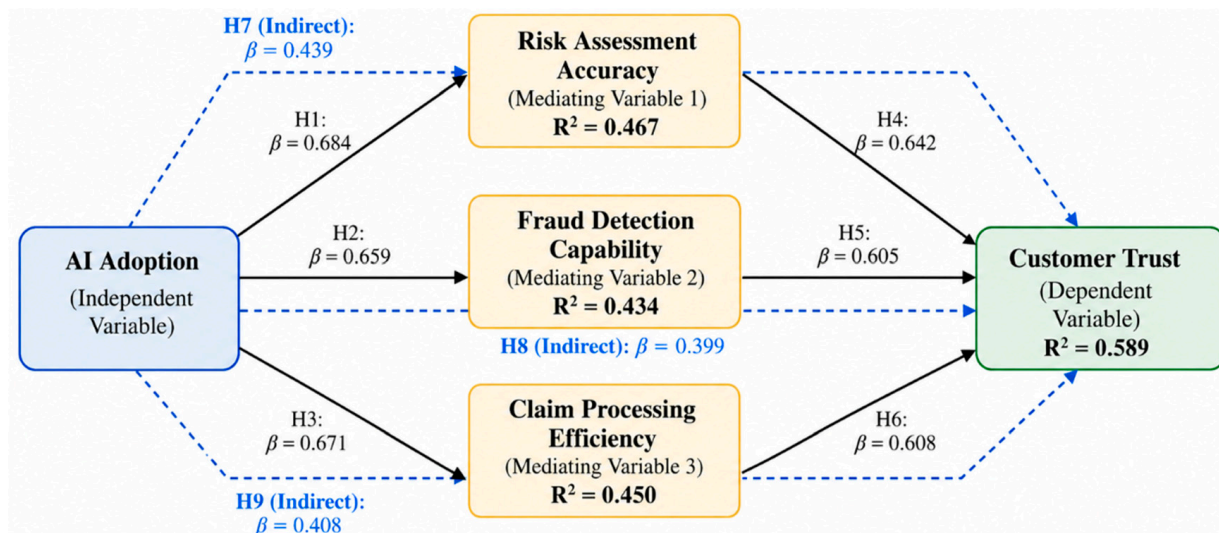


Figure 2. Validated empirical model with standardized path coefficients and coefficients of determination (R^2).

5.6. Discussion of Results

5.6.1. Discussion of H1: AI Adoption and Risk Assessment Accuracy

The findings strongly support H1, indicating a significant positive relationship between AI Adoption and Risk Assessment Accuracy in marine insurance operations ($\beta = 0.684$, $p < 0.001$). These results suggest that respondents reporting higher levels of AI adoption also tend to report higher levels of perceived risk assessment accuracy within marine insurance organizations.

This finding is consistent with previous studies reporting positive relationships between AI technologies, predictive analytics, underwriting quality, and risk evaluation processes within insurance and financial services (Rao & Soofastaei, 2025; Alkhelb & Alshagrawi, 2025). The present findings extend this body of knowledge to the relatively underexplored context of marine insurance, where risk assessment involves the consideration of multiple dynamic factors, including vessel characteristics, cargo information, weather conditions, navigation routes, and port operations (Ali, 2025; Chen et al., 2025).

From the perspective of Dynamic Capabilities Theory, the observed relationship suggests that AI adoption is associated with stronger organizational capabilities related to the identification, interpretation, and evaluation of risk-related information in complex maritime environments. Organizations reporting greater use of AI technologies may therefore be better positioned to process large volumes of information and support risk-related decision-making activities.

The findings also highlight the strategic relevance of data-driven approaches within marine insurance operations. Higher perceived levels of risk assessment accuracy may be associated with more informed underwriting practices, greater consistency in risk evaluation, and stronger confidence in decision-making processes. However, AI should not be viewed as a complete substitute for human expertise. Maritime insurance decisions

frequently require professional judgment, contextual interpretation, and industry-specific knowledge that remain difficult to automate fully. Consequently, the findings suggest that AI technologies and human expertise are likely to play complementary roles within contemporary marine insurance operations.

5.6.2. Discussion of H2: AI Adoption and Fraud Detection Capability

The findings support H2, indicating a significant positive relationship between AI Adoption and Fraud Detection Capability in marine insurance operations ($\beta = 0.659$, $p < 0.001$). These results suggest that respondents reporting higher levels of AI adoption also tend to report stronger fraud detection capabilities within marine insurance organizations.

This finding is consistent with previous studies highlighting positive relationships between AI-based anomaly detection systems, machine learning applications, and fraud identification practices in insurance and financial services (Gupta et al., 2022; Siddiqui & Syed, 2024; Hassan, 2024). The present findings extend this evidence to the marine insurance context, where fraud management frequently involves multiple stakeholders, extensive documentation requirements, and cross-border transactions across different jurisdictions (Dunt, 2024).

From the perspective of Dynamic Capabilities Theory, the observed relationship suggests that AI adoption is associated with stronger organizational capabilities related to the identification and monitoring of potential fraud risks. Organizations reporting greater use of AI technologies may therefore be better positioned to analyze large volumes of operational information and identify unusual patterns requiring further investigation.

The findings also highlight the strategic importance of fraud management within marine insurance operations. Higher perceived levels of fraud detection capability may be associated with greater transparency, stronger control mechanisms, and increased confidence in insurance processes. Effective fraud management remains particularly important in marine insurance because fraudulent activities may generate financial losses and operational disruptions for multiple actors across the maritime ecosystem.

However, while AI technologies provide valuable analytical support, fraud investigations often require legal expertise, contextual interpretation, and professional judgment. Consequently, the findings suggest that AI-based analytical systems and human expertise are likely to play complementary roles in supporting fraud management activities within marine insurance organizations.

5.6.3. Discussion of H3: AI Adoption and Claim Processing Efficiency

The findings support H3, indicating a significant positive relationship between AI Adoption and Claim Processing Efficiency in marine insurance operations ($\beta = 0.671$, $p < 0.001$). These results suggest that respondents reporting higher levels of AI adoption also tend to report higher levels of perceived claim processing efficiency within marine insurance organizations.

This finding is consistent with previous studies reporting positive relationships between AI-based automation technologies and claims management practices within insurance organizations (Rahul, 2022; Alamuri et al., 2025). The present findings extend this evidence to the marine insurance sector, where claims management frequently involves extensive documentation requirements, multiple stakeholders, and complex verification procedures. In such environments, efficient information processing and coordination represent important operational considerations.

From the perspective of Dynamic Capabilities Theory, the observed relationship suggests that AI adoption is associated with stronger organizational capabilities related to information management, operational coordination, and claims handling activities.

Organizations reporting greater use of AI technologies may therefore be better positioned to manage claims-related information and support decision-making processes within complex maritime environments.

The findings further highlight the strategic importance of efficient claims management in marine insurance services. Higher perceived levels of claim processing efficiency may be associated with greater consistency in administrative procedures, improved information accessibility, and stronger perceptions of service responsiveness. These aspects are particularly relevant in marine insurance, where delays in claims handling may affect multiple actors involved in maritime transport and logistics activities.

However, despite the growing role of automation technologies, claims evaluation often requires professional expertise, especially in situations involving legal, contractual, or operational complexities. Consequently, the findings suggest that AI-enabled systems and human expertise are likely to play complementary roles in supporting claims management activities within marine insurance organizations. The combination of technological capabilities and professional judgment may therefore remain an important feature of effective claims handling practices.

5.6.4. Discussion of H4: Risk Assessment Accuracy and Customer Trust

The findings support H4, indicating a significant positive relationship between Risk Assessment Accuracy and Customer Trust in marine insurance services ($\beta = 0.642, p < 0.001$). Among the three operational dimensions examined in this study, Risk Assessment Accuracy exhibits the strongest relationship with Customer Trust, highlighting the importance that stakeholders attach to accurate and reliable risk evaluation within marine insurance services.

This finding is consistent with previous studies suggesting positive relationships between accurate risk assessment practices and perceptions of fairness, competence, and service reliability within insurance and financial service environments (Perkovič et al., 2024; Kadhafi, 2024). In marine insurance, customers frequently encounter complex risk situations that may be difficult to evaluate independently. Consequently, they often rely on insurers' expertise when making insurance-related decisions. Within this context, higher perceived levels of risk assessment accuracy appear to be closely associated with stronger perceptions of professional competence and organizational credibility.

From the perspective of Dynamic Capabilities Theory, the observed relationship suggests that organizations reporting stronger capabilities in risk evaluation also tend to report higher levels of stakeholder trust. The findings indicate that respondents perceive accurate and consistent risk assessment practices as important elements contributing to confidence in marine insurance services.

The findings also suggest that technological investments alone may not be sufficient to explain variations in customer trust. Rather, higher levels of trust appear to be associated with respondents' perceptions of effective operational practices, particularly in relation to risk evaluation activities. Accurate risk assessments may be associated with fairer premium calculations, more transparent underwriting decisions, and greater consistency in insurance processes. As a result, stakeholders may perceive insurance providers as more reliable and professionally competent. Overall, the results highlight the close relationship between risk assessment practices and stakeholder confidence within marine insurance services. The findings therefore reinforce the strategic relevance of accurate risk evaluation as an important organizational capability associated with trust in maritime insurance operations.

5.6.5. Discussion of H5: Fraud Detection Capability and Customer Trust

The findings support H5, indicating a significant positive relationship between Fraud Detection Capability and Customer Trust in marine insurance services ($\beta = 0.605$, $p < 0.001$). These results suggest that respondents reporting stronger fraud detection capabilities also tend to report higher levels of Customer Trust within marine insurance operations.

This finding is consistent with previous studies reporting positive relationships between fraud prevention practices, organizational credibility, and stakeholder confidence (Hassan, 2024; Vemulapalli, 2024; Abdul, 2025). In the context of marine insurance, where transactions often involve multiple actors, international operations, and extensive documentation requirements, the risk of fraudulent claims and information manipulation may represent an important concern (Dunt, 2024). Within such environments, stronger fraud detection capabilities appear to be closely associated with perceptions of transparency, accountability, and organizational reliability.

From the perspective of Dynamic Capabilities Theory, the observed relationship suggests that organizations reporting stronger capabilities in identifying and monitoring potential fraud risks also tend to report higher levels of stakeholder confidence. Effective fraud management practices may contribute to perceptions of operational integrity and support confidence in insurance processes among maritime stakeholders.

The findings also highlight that stakeholder confidence is associated not only with service efficiency but also with perceptions of fairness, security, and transparency. Respondents reporting stronger fraud detection capabilities also tend to report greater confidence in the ability of insurance providers to manage risks responsibly and protect legitimate stakeholders from dishonest practices. In marine insurance environments, where multiple parties are involved in risk-sharing arrangements, these perceptions may play an important role in shaping trust.

However, while AI-supported analytical systems can assist in identifying suspicious patterns and unusual transactions, fraud investigations frequently require professional expertise, contextual interpretation, and legal assessment. Consequently, the findings suggest that technological tools and human judgment are likely to play complementary roles in supporting fraud management activities within marine insurance organizations. Overall, the results highlight the close relationship between fraud detection capability and Customer Trust. The findings therefore reinforce the importance of effective fraud management practices as an organizational capability associated with stakeholder confidence in marine insurance services.

5.6.6. Discussion of H6: Claim Processing Efficiency and Customer Trust

The findings support H6, indicating a significant positive relationship between Claim Processing Efficiency and Customer Trust in marine insurance services ($\beta = 0.608$, $p < 0.001$). These results suggest that respondents reporting higher levels of claim processing efficiency also tend to report higher levels of Customer Trust within marine insurance operations.

This finding is consistent with previous studies reporting positive relationships between service efficiency, responsiveness, timely claims settlement, and stakeholder confidence within insurance and financial service environments (Machireddy, 2022; Gennaioli et al., 2022; Majka, 2024). In marine insurance, claims management represents one of the most visible aspects of service delivery because it directly affects how stakeholders experience insurance coverage and financial protection. Within this context, efficient claims handling appears to be closely associated with perceptions of service quality, reliability, and organizational competence.

From the perspective of Dynamic Capabilities Theory, the observed relationship suggests that organizations reporting stronger claims management capabilities also tend

to report higher levels of stakeholder confidence. Efficient claims processing may reflect an organization's ability to coordinate resources, manage information effectively, and respond to operational requirements in a timely manner. These capabilities are particularly relevant in maritime environments, where claims frequently involve multiple stakeholders, extensive documentation, and complex operational circumstances.

The findings further indicate that respondents place considerable importance on claims management practices when evaluating marine insurance providers. Higher perceived levels of claim processing efficiency are associated with stronger perceptions of responsiveness, consistency, and reliability in insurance services. These perceptions may contribute to stakeholder confidence, particularly when claims involve substantial financial consequences or operational disruptions.

However, despite the growing use of automation technologies, claims evaluation often requires professional expertise, especially in situations involving legal, contractual, or operational complexities. Consequently, the findings suggest that AI-enabled systems and human expertise are likely to play complementary roles in supporting claims management activities within marine insurance organizations. The combination of technological capabilities and professional judgment may therefore remain an important feature of effective claims handling practices. Overall, the results highlight the close relationship between claim processing efficiency and Customer Trust. The findings therefore reinforce the importance of effective claims management as an organizational capability associated with stakeholder confidence in marine insurance services.

5.6.7. Discussion of H7–H9: Mediating Role of Operational Capabilities

The mediation analysis provides additional insights into the mechanisms through which AI Adoption is associated with Customer Trust within marine insurance services. The findings support H7, H8, and H9, indicating that Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency function as significant mediating mechanisms linking AI Adoption to Customer Trust.

Among the three indirect effects, Risk Assessment Accuracy exhibits the strongest mediation effect ($\beta = 0.439$). This finding suggests that the strongest indirect association between AI Adoption and Customer Trust is observed through higher perceived levels of risk assessment accuracy. In marine insurance environments characterized by uncertainty, dynamic operational conditions, and complex risk profiles, stakeholders appear to place considerable importance on insurers' ability to assess risks accurately and consistently. Consequently, organizations reporting greater AI Adoption also tend to report stronger Risk Assessment Accuracy, which is associated with higher levels of Customer Trust.

The mediation effect observed through Claim Processing Efficiency ($\beta = 0.408$) further highlights the importance of operational responsiveness in shaping stakeholder confidence. AI-enabled automation and information-processing capabilities appear to be associated with more efficient claims management practices, which in turn are associated with stronger perceptions of reliability, service quality, and organizational competence. These findings are consistent with previous studies suggesting that efficient service delivery represents an important determinant of trust within insurance and financial service environments.

Similarly, the mediation effect associated with Fraud Detection Capability ($\beta = 0.399$) suggests that AI is associated with Customer Trust through organizations' ability to identify, monitor, and manage fraudulent activities. Respondents appear to associate stronger fraud prevention capabilities with greater transparency, accountability, and organizational integrity. In maritime environments involving multiple stakeholders, extensive documentation requirements, and cross-border transactions, these capabilities may play an important role in reinforcing stakeholder confidence.

From the perspective of Dynamic Capabilities Theory, the mediation results provide strong support for the argument that technological resources are associated with organizational value through the development of operational capabilities rather than through technology alone. AI Adoption represents a strategic technological resource, whereas Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency represent operational capabilities that transform this resource into stakeholder-related outcomes. The findings therefore reinforce the theoretical proposition that organizational capabilities constitute important pathways through which AI-enabled resources are associated with Customer Trust in marine insurance services.

5.6.8. Overall Discussion

The findings of this study provide substantial empirical support for the proposed conceptual framework and highlight significant relationships among AI Adoption, Risk Assessment Accuracy, Fraud Detection Capability, Claim Processing Efficiency, and Customer Trust within the Moroccan marine insurance sector. Collectively, the results suggest that respondents reporting higher levels of AI adoption also tend to report stronger operational capabilities and higher levels of Customer Trust.

The mediation analysis further enriches the interpretation of the findings by demonstrating that the relationship between AI Adoption and Customer Trust operates through multiple operational pathways. The results indicate that Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency function as important mediating mechanisms linking technological adoption to stakeholder confidence. Among these mediators, Risk Assessment Accuracy exhibits the strongest indirect effect, suggesting that improvements in risk evaluation processes represent the most influential pathway through which AI-enabled capabilities are associated with Customer Trust within marine insurance services.

Consistent with Dynamic Capabilities Theory, the findings indicate that the relevance of AI within marine insurance extends beyond the adoption of technology itself and is closely associated with organizational capabilities related to risk evaluation, fraud management, and claims handling activities. The observed relationships suggest that organizations reporting greater utilization of AI technologies also tend to report stronger capabilities across these operational dimensions. The mediation results further demonstrate that these capabilities serve as the primary channels through which AI-generated benefits are translated into stakeholder-related outcomes.

Among the operational dimensions examined, Risk Assessment Accuracy exhibited the strongest direct relationship with Customer Trust and the strongest mediation effect. This finding suggests that stakeholders place particular importance on accurate and reliable risk evaluation when assessing the credibility and reliability of marine insurance providers. Given the complexity and uncertainty that characterize maritime operations, accurate risk assessment appears to represent a critical element in shaping perceptions of professional competence, fairness, and organizational reliability.

The results also highlight the importance of Fraud Detection Capability and Claim Processing Efficiency within the broader marine insurance environment. Respondents reporting stronger capabilities in fraud management and claims handling likewise tend to report higher levels of stakeholder confidence. These findings underscore the importance of transparency, responsiveness, and operational consistency in contemporary marine insurance services. Moreover, the mediation analysis suggests that improvements in these capabilities constitute important pathways through which AI Adoption is associated with Customer Trust.

From a managerial perspective, the findings suggest that AI investments may be most beneficial when accompanied by complementary organizational resources, including employee training, digital infrastructure, data management capabilities, and appropriate governance mechanisms. The results indicate that technology adoption alone may not be sufficient to explain variations in operational capabilities or stakeholder confidence. Rather, the effective integration of technological and organizational resources appears to be closely associated with more favorable perceptions of operational performance and trust.

At the same time, the findings reinforce the continuing importance of human expertise within marine insurance operations. Although AI technologies provide valuable analytical support, many insurance activities continue to require professional judgment, contextual interpretation, and industry-specific knowledge. Consequently, the results suggest that AI-enabled tools and human expertise are likely to play complementary roles within marine insurance organizations.

The findings are particularly relevant for emerging maritime economies such as Morocco, where increasing digitalization, expanding port activities, and evolving risk environments are creating growing interest in advanced insurance technologies. Within this context, the observed relationships highlight the potential relevance of AI-supported practices for organizations seeking to strengthen operational capabilities and stakeholder confidence in marine insurance services. Overall, the study demonstrates that the benefits associated with AI Adoption are not limited to technological modernization itself but are closely associated with the development of operational capabilities that, in turn, are linked to higher levels of Customer Trust.

6. Conclusions

This study examined the relationships among Artificial Intelligence (AI) Adoption, Risk Assessment Accuracy, Fraud Detection Capability, Claim Processing Efficiency, and Customer Trust within the Moroccan marine insurance sector. Focusing on the strategic maritime hubs of Tangier Med and Casablanca, the study developed and empirically evaluated a conceptual framework linking AI adoption, operational capabilities, and customer trust. The findings indicate significant positive relationships among the examined constructs. In particular, respondents reporting higher levels of AI adoption also tended to report stronger capabilities in risk assessment, fraud detection, and claims processing. Furthermore, the mediation analysis indicated that Risk Assessment Accuracy, Fraud Detection Capability, and Claim Processing Efficiency function as important mediating variables in the relationship between AI Adoption and Customer Trust. Among these mediators, Risk Assessment Accuracy exhibited the strongest indirect effect, highlighting the central role of accurate risk evaluation as a factor associated with higher levels of stakeholder confidence within marine insurance services. These findings provide empirical evidence supporting the relevance of AI-enabled practices within maritime insurance operations and contribute to a better understanding of how AI adoption is associated with stakeholder-related outcomes through the development of operational capabilities in a sector that remains relatively underexplored in the existing literature.

From a theoretical perspective, this study contributes to the growing body of knowledge on AI adoption in insurance by extending existing research to the specific context of marine insurance. Guided by Dynamic Capabilities Theory, the findings support the relevance of organizational capabilities in understanding the relationships among technological resources, operational practices, and stakeholder perceptions. More specifically, the mediation results reinforce the argument that technological resources are associated with organizational value through the development of operational capabilities rather than through technology alone. The findings suggest that AI-enabled operational capabilities

represent important mechanisms through which technological resources are associated with customer trust. The study also contributes to the limited literature examining AI applications within emerging maritime economies and provides empirical evidence from Morocco, thereby expanding the geographical and sectoral scope of current research. More broadly, the results highlight the importance of considering both technological and organizational dimensions when examining AI-related developments in complex maritime environments.

The findings also have several practical implications for stakeholders operating within the maritime insurance ecosystem. For insurance companies, the results highlight the importance of integrating AI-supported tools into risk evaluation, fraud management, and claims handling activities while maintaining appropriate levels of professional oversight and human judgment. The mediation results further suggest that the potential benefits associated with AI adoption may be more evident when technological investments are accompanied by stronger operational capabilities. Investments in employee training, data governance, digital infrastructure, and analytical competencies may therefore facilitate the effective integration of AI technologies within insurance operations. For port authorities and shipping companies, AI-supported information systems, digital documentation platforms, and data-sharing mechanisms may support greater operational visibility, improved information quality, and more effective coordination among maritime stakeholders. Enhanced collaboration between insurers, port authorities, and shipping operators may be associated with greater transparency and more efficient maritime risk management practices. From a regulatory perspective, the findings underline the growing importance of establishing governance frameworks that address AI transparency, auditability, cybersecurity, accountability, and regulatory oversight. As AI applications become increasingly integrated into insurance processes, appropriate regulatory mechanisms may help ensure fairness, transparency, data protection, and stakeholder confidence while promoting responsible innovation within maritime insurance services.

Despite its contributions, this study has several limitations that should be acknowledged. First, the use of a cross-sectional research design limits the ability to establish causal relationships among the examined constructs. Consequently, the findings should be interpreted as statistically significant associations based on respondents' perceptions rather than definitive evidence of causality. Second, the study employed a purposive sampling strategy focused on professionals operating within the ports of Tangier Med and Casablanca. Although this approach ensured the participation of knowledgeable respondents, it may limit the generalizability of the findings to other maritime contexts and geographical regions. Third, the study relied exclusively on self-reported survey data. Although several procedural and statistical remedies were implemented to reduce common method bias, including anonymity assurances, questionnaire design procedures, non-response bias assessment, and Harman's Single-Factor Test, the possibility of residual common method variance cannot be entirely excluded. Fourth, the study assessed respondents' perceptions regarding operational capabilities and customer trust rather than objective organizational performance indicators, which may limit the ability to directly evaluate actual organizational outcomes. Finally, although mediation effects were examined, future studies employing longitudinal designs would be better positioned to verify the temporal sequencing of the proposed relationships and provide stronger evidence regarding the mechanisms through which AI adoption is associated with customer trust.

Future research could address these limitations by incorporating longitudinal research designs, objective operational performance indicators, and comparative international datasets. Qualitative interviews, case studies, and mixed-method approaches would also provide deeper insights into AI adoption processes, organizational practices, and decision-making activities within marine insurance organizations. Future studies may

also employ more advanced mediation analyses and longitudinal modeling approaches to further investigate the mechanisms through which AI-enabled capabilities influence customer trust and other organizational outcomes. Furthermore, comparative studies involving multiple maritime economies would provide valuable opportunities to examine whether the relationships observed in this study remain consistent across different institutional, regulatory, and operational environments. Future research may also explore the combined application of AI with emerging technologies such as blockchain, the Internet of Things (IoT), digital twin systems, and advanced maritime analytics to further examine their relevance for maritime risk management and insurance services.

Overall, the findings highlight significant relationships among AI Adoption, operational capabilities, and Customer Trust within the Moroccan marine insurance sector. The results suggest that organizations reporting greater use of AI technologies also tend to report stronger capabilities in risk assessment, fraud management, and claims handling activities, which are in turn associated with higher levels of Customer Trust. The findings therefore suggest that the value associated with AI adoption extends beyond technological implementation itself and is closely linked to the development of operational capabilities that are associated with higher levels of stakeholder confidence. These results provide useful insights for insurers, maritime operators, port authorities, and policymakers seeking to better understand the role of AI-supported practices within contemporary marine insurance environments. As digital transformation continues to reshape maritime industries, understanding the relationships among technological adoption, operational capabilities, and customer trust will remain an important area for both research and professional practice.

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