“Artificial intelligence adoption, transparency, and organizational change in GCC insurers: Disclosure-based evidence”

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ARTIFICIAL INTELLIGENCE ADOPTION, TRANSPARENCY, AND ORGANIZATIONAL CHANGE IN GCC INSURERS: DISCLOSURE-BASED EVIDENCE

Abstract

Artificial intelligence is diffusing across Gulf Cooperation Council insurance markets, yet disclosure-based evidence remains fragmented on whether adoption is associated with organizational change or localized automation. This study examines a purposive disclosure-based sample of 120 insurers from Saudi Arabia, the United Arab Emirates, Qatar, Kuwait, Oman, and Bahrain. Because inclusion required sufficient disclosure of artificial intelligence practices, the sample is not intended to represent the insurance market. The study examines whether disclosed artificial intelligence adoption is associated with organizational change through financial transparency and operational efficiency. The dataset is constructed from annual reports, audited financial statements, governance reports, environmental, social, and governance reports, investor materials, and regulatory documents. Documents from 2017 to 2023 are treated as an observation window, coded at the item level, and aggregated into one firm-level score per insurer for cross-sectional structural equation modeling. Results indicate positive associations from artificial intelligence adoption to financial transparency ($\beta = 0.52$, $p < 0.001$) and operational efficiency ($\beta = 0.49$, $p < 0.001$). Financial transparency ($\beta = 0.41$, $p = 0.003$) and operational efficiency ($\beta = 0.38$, $p = 0.012$) are associated with organizational change. The indirect paths through transparency and efficiency are statistically distinguishable from zero within the model. Because all variables are derived from similar disclosure evidence, the pattern is interpreted as disclosure co-patterning rather than proof of a mechanism. The findings are associational, not causal, representative, or longitudinal.

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INTRODUCTION

Insurance markets are undergoing rapid digitalization as artificial intelligence (AI) is applied to underwriting, claims management, fraud analytics, pricing, customer service, and compliance monitoring. In the GCC, this transformation is important because insurers operate within supervised financial systems shaped by the Saudi Central Bank/Insurance Authority, the Central Bank of the UAE, the Qatar Central Bank, the Kuwait Insurance Regulatory Unit, the Oman Financial Services Authority, and the Central Bank of Bahrain. Such regulatory bodies expect firms to prove their solvency, consumer protections, governance quality, data accuracy, and operational accountability. Therefore, adopting AI must be considered both an investment and a change that affects organizational transparency, auditability, interpretability, and control. Regional banking evidence also indicates that AI and big-data applications are reshaping accounting processes and data-driven decision making, while continuing to raise data-quality, infrastructure, and ethical concerns (Bader et al., 2025).

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In other words, the scientific problem addressed in this study is how adopting AI translates into organizational change in the context of insurance. Previous empirical studies tend to consider AI adoption as a unitary technological indicator and measure its influence on organizational performance or digital transformation. However, such an approach leads to a gap in measurement and explanation. Insurance organization change refers to tangible decision-making processes, modified underwriting and claims processes, evidence of reporting processes, redesigned control systems, and necessary competencies for monitoring. An adoption intensity indicator cannot show whether AI adoption translates into actual organizational change or is limited by automated processes. Furthermore, a major limitation is the isolation of two different streams in empirical research. One research stream is devoted to the operational benefits of using AI, such as automation, case prioritization, resource allocation, and efficiency. Another stream is concerned with governance challenges, such as transparency, interpretability, fairness, documentation, and compliance. If these two streams were analyzed independently, it is unclear why some companies achieve a sustainable organizational change after adopting AI and others merely benefit from operational efficiency.

For these reasons, this paper introduces a careful, disclosure-oriented account of AI-driven organizational change in GCC insurers. The paper explores whether AI adoption announced by insurers is associated with organizational changes in terms of financial transparency and operational efficiency, and whether the process can be seen in the evidence provided by public governance and management-control systems. It should be pointed out that the paper does not seek to document all internal AI systems and measure the annual dynamics of their use. Moreover, there might be an additional pattern that should be observed: if certain insurers are characterized by high levels of AI disclosure, they might have higher levels of governance, efficiency, and organizational change disclosures as well.

1. LITERATURE REVIEW

The increasing reliance on artificial intelligence (AI) in various aspects of insurance, including underwriting, claims management, fraud detection, pricing, customer service, compliance monitoring, and reporting, turns AI into one of the main topics of recent insurance research, which treats AI not as a peripheral tool, but as a capability that can influence risk allocation, documentation, and accountability (Braun & Jia, 2025). The unresolved problem is that of disclosure-related organizational transformation.

The InsurTech literature explains how digital tools transform insurance processes through platform services, automated analytics, and customer interactions (Ahmad et al., 2025; Zarifis et al., 2023). The problem is that organizational transformation is mostly considered on the industry-wide level in the literature, whereas little attention is paid to whether companies redesign their documentation, decision rights, workflow escalation, and audits following AI adoption.

AI adoption research clarifies reasons for earlier and fuller adoption in various insurers. From the technology-organization-environment perspective, readiness, capability, and external push are highlighted, while strategy literature compares incumbent firms' and newcomers' digitalization trajectories (Gupta et al., 2022; Holland & Kavuri, 2025). However, adoption is not transformation per se. AI technologies may become merely pilot projects or a signaling effort.

Insurance-relevant research suggests that adoption is related to usefulness perception, data quality, support from managers, capabilities of employees, and credibility of regulation (Zaijuan et al., 2025). The problem is that measuring adoption through disclosure language implies assessing the complexity and sophistication of disclosure rather than the operational depth of AI adoption.

The adoption barriers literature further highlights this problem. Legacy systems, data fragmentation, ambiguous governance ownership, inadequate skills, and regulatory challenges can prevent AI use in insurers (da Silva Tavares et al., 2025; Acosta-Prado et al., 2024). In other words, adoption barriers separate AI announcement and adoption. For this reason, coding should cover process integration, control-related information, and capability development.

In turn, the AI governance literature provides a necessary accountability perspective. Reviews emphasize transparency, responsibility, risk monitoring, and human-in-the-loop principles as prerequisites of reliable AI deployment (Birkstedt et al., 2023; Batool et al., 2025). The value of this literature is conceptual richness, but the need is to translate AI governance principles into the insurance context due to algorithmic decision making in underwriting, claims, pricing, fraud analytics, and consumer relations.

Specifically, financial-services-related AI governance studies narrow the scope of analysis by integrating AI with digital governance, compliance, ethical standards, and regulatory technology (Bagherifam et al., 2025). This body of literature justifies analyzing AI in terms of compliance and control. However, public governance disclosure does not always signify substance. Hence, disclosure bias is the key methodological concern.

From the transparency perspective, financial-services-oriented AI transparency studies stress that AI can contribute to information consistency, audit quality, and reporting reliability by providing data lineage, anomaly identification, and governance documentation (Shaban & Omoush, 2025; Zhao et al., 2024). Nonetheless, transparency is more than just information quantity. Transparency must be captured through auditability, consistency, timeliness, and traceability. The decision relevance of disclosure is also context dependent, as Jordanian evidence indicates that financial information can exert a stronger influence on investment decisions than non-financial information (Alshehadeh et al., 2025).

Insurers' underwriting and pricing are examples of the efficiency-accountability tension. Usage-based insurance and machine learning can improve segmentation, pricing accuracy, and personalization (Alfiero et al., 2022; Dong & Quan, 2025). However, the increased precision can limit contestability because of obscure decision criteria, model logic, and uncertain data sources. In other words, this example demonstrates that adoption is one thing and transparency is another.

The fairness research reveals the importance of this distinction. AI in underwriting and claims processing can result in unfairness, discrimination, and harm to consumers, which is why explainability, review, and appeal are needed (van Bekkum et al., 2025; Zheng et al., 2025). This body of literature pushes the conversation beyond AI performance and emphasizes control-related routines as the key criteria for transformation.

Telematics and sensor data studies contribute a market perspective and a regulatory one. Sensor-based insurance involves changes in insurance policies, while telematics pricing challenges rate-regulation assumptions (Soleymanian et al., 2025; Xie, 2024). As a result, AI in insurance is not merely a matter of back-office technology. On the contrary, AI can also impact pricing justification, consumer confidence, and supervisory scrutiny.

As for claims and fraud analytics, AI is associated with efficiency through automation and improved risk assessment via machine learning in high-frequency data environments (Vinora et al., 2024; Vorobyev, 2024). Nonetheless, operational efficiency relies on documentation of exceptions, disputes, and human review. Therefore, efficient process improvement is an outcome of control rather than mere automation.

Consumer-oriented AI technologies involve humanoids and AI-based communication channels, which can help increase responsiveness and consistency, but the success of such technologies depends on factors such as trust, usefulness, privacy, and reliable communication (Patil et al., 2024; de Andrés-Sánchez & Gené-Albesa, 2025). This line of research demonstrates how automation affects consumer routines, but it provides no insights into financial transparency and control issues. Related evidence on Facebook use further shows that digital engagement depends on users' motives, perceived features, and achieved gratifications, underscoring the importance of stakeholder reception in technology-enabled communication (Oreqat, 2021).

Evidence from Jordanian insurance reveals the influence of business intelligence on the reduction of data silos if supported by leadership and corporate culture. Moreover, non-life insurance literature shows that the efficiency of insurers contributes to their financial resilience (Abu-AlSondos, 2025; Ige-Gbadeyan & Swanepoel, 2025). As a result, AI

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adoption becomes important in the context of process integration, control, and efficiency.

The knowledge management and InsurTech trend analysis literature confirms the role of coordinated efforts in digital transformation (Elgargouh et al., 2024; Lee & Yim, 2025). The value of this literature is its emphasis on learning and cooperation. However, the drawback is limited empirical analysis and a general market perspective. Hence, it is appropriate to respond to this body of research with firm-level quantitative analysis.

In this respect, ecosystem and market response literature offers interesting insights. InsurTech ecosystems imply coordination among insurers, technology providers, regulators, and customers, while reactions to digitalization demonstrate that digitalization announcements are read differently depending on expectations (I. Sosa & S. Sosa, 2025; Ma & Ren, 2023). The point is that disclosure signals have strategic value in terms of organizational transformation.

General market-level studies highlight the impact of InsurTech innovation on insurance markets and investment decisions. Such research reveals that innovations transform traditional financial market practices depending on market structures and institutions (Bian et al., 2023; Eti et al., 2024). The contribution of these studies is in justifying the focus on GCC insurers as a single group.

Financial AI literature provides additional insights, which come from the analysis of technological transformation and compliance issues (Aldasoro et al., 2025; Syed et al., 2025). Transparency and efficiency become important criteria in terms of technological transformation, while the need for auditing is emphasized in the context of compliance. This means that transparency and efficiency must be treated as mediating mechanisms between adoption and organizational change.

The ethics governance literature highlights the need for human judgement in deploying AI, while GCC-insurance-related evidence suggests that AI governance is closely connected to leadership, oversight, and decision-making accountability (Gamerdinger & Willers, 2025). A firm can have highly developed technical capabilities and still show poor control and oversight.

For the GCC context, it is important that insurers face similar challenges of digitalization but different supervisory and disclosure environments. GCC evidence emphasizes the link between auditing tools and governance, while Saudi Arabia's evidence focuses on InsurTech and e-commerce integration, cybersecurity, and real-time risk assessment (Yaseen & Al-Amarneh, 2025; Khrais, 2025). However, research gaps remain.

Finally, emerging-market financial AI literature offers more information about AI adoption in the GCC region. Specifically, evidence related to Bahrain discusses behavioral and institutional factors contributing to AI adoption in the context of accounting and reporting. At the same time, broader evidence suggests that financial AI adoption is associated with governance, capability, and institutional preparedness.

In addition, regional studies on governance and assurance confirm the control perspective. GCC-focused AI investment research emphasizes issues of governance and risk assessment, while evidence from internal auditing focuses on compliance and value-added assurance (Morshed, 2024a; Shaban & Barakat, 2023). These studies support the control perspective, but they do not analyze item-level disclosure data.

Finally, there is regional accounting and insurance disclosure literature, which shows the increasing relevance of AI-assisted accounting systems and insurance governance in the context of GCC reporting (Morshed, 2024b). While this literature is very close to the present approach, it lacks a firm-level analysis of adoption, transparency, efficiency, and organizational change.

Thus, the reviewed literature supports an integrated but critical approach. AI adoption may constitute a strategic organizational capability, but its value depends on information flows, process design, decision-making routines, and effective supervision. However, the literature has not adequately explained how AI adoption, financial transparency, operational efficiency, and organizational change operate jointly within a disclosure-based framework.

The disclosure-based design offers both analytical advantages and important limitations. Annual reports,

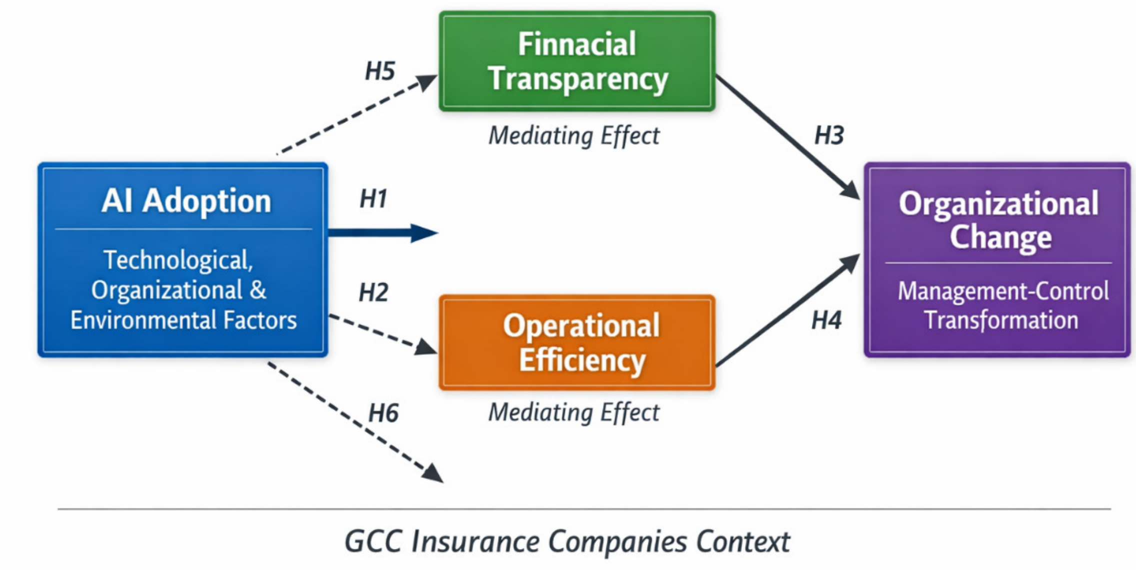

Figure 1. Conceptual framework linking AI adoption, financial transparency, operational efficiency, and organizational change

audited financial statements, governance disclosures, environmental, social, and governance reports, and regulatory materials provide systematic and externally observable evidence. Nevertheless, disclosure bias may arise because all four constructs are measured from similar publicly available information that firms can selectively manage for reporting purposes. Consequently, the structural relationships are interpreted as disclosure-based organizational associations rather than evidence of causal mechanisms, while reporting sophistication and selective disclosure remain plausible alternative explanations.

Accordingly, the aim of this study is to examine whether disclosed AI adoption is associated with organizational change in GCC insurers, both directly and indirectly through disclosed financial transparency and operational efficiency, using these four dimensions as latent constructs within a structural equation model.

Based on the objective and literature review, the hypotheses are as follows:

H1: Disclosed AI adoption is expected to be positively associated with disclosed financial transparency in insurance companies.

H2: Disclosed AI adoption is expected to be positively associated with disclosed operational efficiency in insurance companies.

H3: Disclosed financial transparency is expected to be positively associated with disclosed organizational change in insurance companies.

H4: Disclosed operational efficiency is expected to be positively associated with disclosed organizational change in insurance companies.

H5: Disclosed financial transparency is expected to form an indirect disclosure-based pathway between AI adoption and organizational change in insurance companies.

H6: Disclosed operational efficiency is expected to form an indirect disclosure-based pathway between AI adoption and organizational change in insurance companies.

2. METHOD

This study employs a disclosure-based, cross-country quantitative design to examine AI-enabled transformation signals in the GCC insurance industry. The unit of analysis is the insurance company. AI adoption is defined as the disclosed use of AI-enabled systems in underwriting/risk selection, claims triage, fraud analytics, customer-service automation, compliance support, or reporting routines. Financial transparency refers to disclosed traceability, timeliness, consistency, and

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auditability of information flows. Operational efficiency refers to disclosed process improvements in time, cost, automation depth, or workflow standardization. Organizational change refers to the disclosed redesign of control routines, performance metrics, decision rights, staff capabilities, and governance procedures. Structural equation modeling (SEM) estimates the relationships among latent constructs at the firm level. The empirical design is cross-sectional because each insurer enters the SEM once after aggregation of the 2017–2023 disclosure evidence.

Data are constructed from insurance-company disclosures for 2017–2023, including annual reports, audited financial statements, governance reports, sustainability/ESG reports, investor presentations where available, and regulatory filings or supervisory documents. This disclosure-based design is consistent with corporate-report research on algorithmic decision-making disclosures (Bonsón et al., 2023). The regulatory-document base covers materials linked to the Saudi Central Bank/Insurance Authority, the Central Bank of the UAE, Qatar Central Bank, Kuwait Insurance Regulatory Unit, Oman Financial Services Authority, and the Central Bank of Bahrain. The years 2017–2023 define the disclosure observation window rather than a panel model. Each insurer-year document set was coded at the item level, annual construct scores were calculated, and one firm-level SEM input was then formed for each insurer. The firm-level score equals 0.4 x the average annual construct score for 2017–2023 plus 0.6 x the 2023 endpoint score. The weight of the 2023 endpoint is higher than 2017–2022 because 2023 represents the most recent year when all audited disclosures for the year would have been available and represent cumulative evidence regarding visibility of AI governance and operation processes, while 2017–2023 is kept to preserve the historical disclosure trail of the firms. Subsequent years were excluded to maintain consistency between the full audited year and interim or partial disclosures. The purposive sample consists of GCC insurance companies that provided sufficient public evidence of adopting AI. Six GCC countries were selected to capture different levels of institutional maturity and technological infrastructure within the region. The purposive disclosure-based sample includes 120 insurance companies distributed across the following countries: Saudi Arabia (30 companies), UAE (25 companies), Qatar (20 companies), Kuwait (15 companies), Oman (15 companies), and Bahrain (15 companies). Insurers were included when their available annual/audited public documents provided sufficient AI adoption evidence and the evidence for the indicators. Since the sample relied on the availability of the public disclosure of AI evidence, the sample includes insurance companies that disclose such information and should not be seen as representing all GCC insurance companies (Morshed, 2025).

The purposive sample was generated based on the verifiable disclosure of the adoption of AI for operational or compliance purposes in insurance, such as underwriting or risk selection, claims triage and processing, fraud detection, customer service automation, and compliance or reporting activities. The criterion for inclusion was that the insurers must report AI adoption in operational or compliance-related processes. Exclusions were based on a lack of AI adoption evidence, absence of annual or audited materials, and insufficient indicators for the construct development. Regulatory documents at the country level were utilized as a measure of the enabling environment. These regulatory documents are used in the context of supervisory expectations and not as individual firm-level observations.

To ensure consistency across the countries and individual insurers, two independent coders were asked to code the disclosures following the structured coding instrument. The coding instrument was designed to measure AI application, automation degree, audit trail and documentation indicators, transparency indicators, efficiency indicators, and organizational change. Items were individually coded based on textual evidence from disclosed documents and not on any external market statements. The interrater reliability assessment was conducted using Cohen's kappa = 0.84, suggesting a good coding reliability. Disagreements were discussed to reach an agreement and resolve the coding issue. Such a coding protocol was recommended recently for qualitative studies (Cole, 2024). In addition, disclosure coding and analysis are often advised to be accompanied by coding agreement reporting and disagreements adjudication procedures (Cofie et al., 2022). The final disclosure coding instrument workbook includes the list of insured companies, document inventory, itemized yearly matrix of coding, aggregation worksheet, and examples of the coding decisions that will allow replication and review of the disclosure transformation process. This procedure ensures better consistency; however, it does not prevent the disclosure-sophistication alternative explanation. The exclusion of external market statements is additionally justified by evidence that information flows across traditional and new media may be affected by misinformation and uneven source reliability (Al-Muntasir, 2022).

The adopted methodological approach implies the construction of three disclosure-based constructs that include six raw disclosure items each (six AI adoption indicators, five financial transparency indicators, four operational efficiency indicators, and five organizational change indicators) (Ain et al., 2019). The measurement for each variable includes coding of raw evidence on a 0-3 ordinal scale where 0 indicates lack of disclosure, 1 indicates presence of generic digitalization or automation language, 2 indicates AI or related practice or procedure mentioned specifically, and 3 indicates that the AI or practice or procedure is linked to specific workflow integration, governance, control, documentation, escalation, implementation details, or performance monitoring. The item mean is then translated into the 1-5 construct score used in the SEM as follows:

$$Construct\ Score_i = 1 + \left(3x_i\right) \cdot 4. \quad (1)$$

The full matrix of item-level decisions is presented in the supplement workbook. This methodological description explains the conversion process of public textual evidence into numerical latent variables.

Since all of the measured variables in the study are constructed based on public disclosure data and evidence logic behind each item, the research methodology is subject to alternative interpretation, namely, that of disclosure sophistication, as the more sophisticated firms tend to provide more detailed disclosures than less mature firms. In order to mitigate this potential concern, the coding instrument was designed to keep all evidence-based items separated by domain, where AI evidence was coded separately from auditability evidence, efficiency evidence, and organizational redesign. Even so, the separation was unable to fully distinguish AI adoption practice from the general tendency of mature firms to disclose more information and data in all possible aspects. Therefore, the paths found in the SEM model and its indirect effects should be viewed as disclosure-based co-occurrence patterns rather than the actual causal effect of AI adoption.

The matrix of item coding contains 840 rows (120 firms × 7 years) for each observed variable (6 AI adoption, 5 financial transparency, 4 operational efficiency, 5 organizational change). Each year is individually coded at the item level. Then, annual construct means are computed and converted to the 1-5 scale, and then the construct scores for each firm are aggregated based on these 7 yearly values. Note that where decimals appear, they are averaged coder scores or construct annual calculations based on a 0-3 scale scoring. The full 840 × 20 matrix is reported in the supplement since it has too many rows and cells to fit in Appendix B. Representative examples are reported in Appendix B. In contrast, Appendix B contains only excerpts from itemized company-level coding. Full codes include company ID, source document type, source document year, company name, document title, source document reference, document type class, evidence score, and coding rationale.

The empirical model is specified using a standard SEM formulation that distinguishes between the measurement model and the structural model. The measurement model links observed disclosure indicators to latent constructs and is written as:

$$x = \Lambda \eta + \varepsilon, \quad (2)$$

where x is the vector of observed disclosure indicators, Λ is the factor-loading matrix, η is the vector of latent constructs (AI adoption, financial transparency, operational efficiency, and organizational change), and ε represents measurement error.

The structural relations among latent constructs are expressed as:

$$\eta = B\eta + \Gamma \xi + \zeta, \quad (3)$$

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where η contains the endogenous latent variables (financial transparency, operational efficiency, and organizational change), B is the matrix of structural path coefficients among endogenous constructs, ξ contains the exogenous latent driver (AI adoption), Γ represents effects from exogenous to endogenous constructs, and ζ represents structural disturbances.

Consistent with the directional expectations examined in this study, this matrix form corresponds to the insurance-company structural equations:

$$Financial\ transparency = \beta_1 \cdot AI + \zeta_1, \quad (4)$$

$$Operational\ efficiency = \beta_2 \cdot AI + \zeta_2, \quad (5)$$

$$\begin{aligned} &Organizational\ change \\ &= \beta_3 \cdot Financial\ transparency \\ &+ \beta_4 \cdot Operational\ efficiency + \zeta_3, \end{aligned} \quad (6)$$

where the coefficients quantify how disclosed AI adoption is associated with transparency and efficiency in insurance operations (*H1-H2*), and how these mechanisms are associated with organizational change (*H3-H4*), interpreted as management-control transformation within insurers.

Indirect pathways are estimated by calculating the products of constituent paths. The indirect effect through transparency is computed as:

$$Indirect\ effect\left(transparency\right) = \beta_1 \cdot \beta_3, \quad (7)$$

and the indirect effect through efficiency is computed as:

$$Indirect\ effect\left(efficiency\right) = \beta_2 \cdot \beta_4, \quad (8)$$

with indirect-effect uncertainty assessed using 5,000-sample bootstrapped confidence intervals. Because all variables are disclosure-derived, these indirect estimates are interpreted as model-based disclosure pathways rather than causal mediation effects.

Estimation proceeds in two stages. First, the measurement model is evaluated through Confirmatory Factor Analysis (CFA) to establish factor structure, internal consistency, convergent validity, and discriminant validity. Reliability, convergent validity, and discriminant validity are reported in accordance with structural equation modeling measurement-reporting recommendations (Cheung et al., 2024). Second, the structural model is estimated using robust maximum likelihood with bootstrapping to test the direct and mediated effects. Model adequacy is evaluated using fit criteria including CFI and TLI above 0.90, RMSEA and SRMR below 0.08, and HTMT below 0.85 for discriminant validity. HTMT is retained because it provides a focused assessment of latent-construct separation in structural equation modeling (Roemer et al., 2021).

Country-level differences are reported descriptively because the country-level subsamples are unequal and small, especially for Kuwait, Oman, and Bahrain. Formal multi-group analysis and measurement-invariance claims are therefore not retained in the reported empirical model. This helps to maintain consistency between the Method and Results sections and prevents the presentation of cross-country paths that have not been adequately estimated and analyzed.

Finally, Bayesian SEM will be used as a robustness validation test to establish the stability of the estimates under moderate sample sizes and latent variable complexities. Bayesian analysis takes the form of a posterior distribution:

$$p\left(\theta \mid D\right) = \frac{p\left(D \mid \theta\right) p\left(\theta\right)}{p\left(D\right)}, \quad (9)$$

where θ is the parameter vector; D is the data, in this case the insurance-disclosures dataset; $p(\theta)$ is the prior distribution; $p(D \mid \theta)$ is the likelihood; $p(D)$ is the marginal likelihood; and $p(\theta \mid D)$ is the posterior distribution. The posterior summary (mean or median and 95% credible interval) will be provided for the structural coefficients. Estimation is performed using MCMC simulation with 20,000 iterations, where convergence will serve as the criterion for making the decisions.

The full supplementary coding workbook has been uploaded to Zenodo to ensure openness and reproducibility. The uploaded document includes the 120-company sample list, document list, references, 840 company-year item-level coding, coding instructions, aggregation worksheet, representative coding examples, firm-level structural equations model inputs, and sensitivity/bias check. Researchers can see how the 2017–2023 disclosures were coded and translated into quantitative scores of the constructs (Morshed, 2026).

3. RESULTS

The following subsection discusses the empirical results of the proposed firm-level disclosure model. Specifically, it provides descriptive statistics; measures the validity and reliability of the measurement model; provides structural coefficient estimates for the directional hypotheses and indirect disclosure pathways; reports R^2 values from the SEM spreadsheet; and conducts robustness tests on the model and checks the potential biases from using only positive paths as causal evidence. The data set included 120 insurance firms from six GCC countries with inclusion criteria that included AI adoption and use in underwriting or risk selection processes, claims processing and triage, fraud detection, customer service automation, and compliance or reporting functions. These insurers came from Saudi Arabia (n = 30); UAE (n = 25); Qatar (n = 20); Kuwait (n = 15); Oman (n = 15); and Bahrain (n = 15). Table 1 provides an overview of the country-level means and standard deviations of disclosure scores. Note that the statistics here provide information about the aggregated firm-level data rather than year-by-year panels or representative country-level markets. As shown in Table 1, the UAE had the highest mean score for AI adoption (M = 4.32), and Saudi Arabia followed with M = 4.18. Financial transparency was higher in Bahrain (M = 4.21) and the UAE (M = 4.12). The average scores across firms were 3.91 for AI adoption, 4.01 for financial transparency, 3.93 for operational efficiency, and 3.91 for organizational change.

Findings of Confirmatory Factor Analysis (CFA) were adequate in terms of construct measurement. As shown in Table 2, standardized factor loadings surpassed 0.70 for all constructs, composite reliability spanned from 0.88 to 0.93, AVE ranged from 0.65 to 0.78, and Cronbach's Alpha was from 0.86 to 0.91. Discriminant validity was also acceptable (HTMT < 0.85), while the general fit indices of the measurement model were good (χ^2 / df = 1.94; RMSEA = 0.046; CFI = 0.971; TLI = 0.963; SRMR = 0.041). These fit indices can be interpreted as satisfactory fit of the model, yet the latter is not proved mechanically since arbitrary cutoff values should be considered in light of design specifics (McNeish & Wolf, 2023). CFA proved statistical construct separation, but it cannot solve the issue of the potential common source bias introduced by utilizing publicly available information as an indicator of all constructs.

The structural model fit the firm-level disclosure-based model appropriately (χ^2 / df = 2.03; RMSEA = 0.049; CFI = 0.967; TLI = 0.958; SRMR = 0.046).

Table 1. Country-level descriptive statistics for AI adoption, transparency, efficiency, and organizational change in GCC insurance companies

Country	n	AI adoption M (SD)	Transparency M (SD)	Efficiency M (SD)	Change M (SD)
Saudi Arabia	30	4.18 (0.47)	4.07 (0.44)	4.15 (0.42)	4.09 (0.43)
UAE	25	4.32 (0.41)	4.12 (0.46)	4.09 (0.39)	4.12 (0.40)
Qatar	20	3.95 (0.45)	4.10 (0.42)	3.88 (0.47)	3.85 (0.45)
Kuwait	15	3.34 (0.52)	3.72 (0.51)	3.65 (0.49)	3.61 (0.48)
Oman	15	3.21 (0.50)	3.68 (0.48)	3.59 (0.53)	3.57 (0.46)
Bahrain	15	3.87 (0.48)	4.21 (0.43)	3.92 (0.46)	3.89 (0.44)
Overall	120	3.91 (0.60)	4.01 (0.48)	3.93 (0.49)	3.91 (0.48)

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Table 2. Reliability and validity results for disclosure-based insurance-company constructs

Construct	CR	AVE	Cronbach's alpha	Factor loading range
AI adoption	0.91	0.72	0.89	0.74-0.88
Financial transparency	0.93	0.75	0.91	0.77-0.90
Operational efficiency	0.88	0.65	0.86	0.70-0.84
Organizational change	0.90	0.68	0.88	0.72-0.85

Based on Table 3, higher AI adoption ($\beta = 0.52$, $p < 0.001$) is positively correlated with both financial transparency ($\beta = 0.52$, $p < 0.001$) and operational efficiency ($\beta = 0.49$, $p < 0.001$). Moreover, the analysis revealed that higher financial transparency ($\beta = 0.41$, $p = 0.003$) and higher operational efficiency ($\beta = 0.38$, $p = 0.012$) are positively correlated with organizational change. However, caution must be exercised regarding the interpretation of these findings because structural equation modeling effects have to be interpreted considering the situation instead of meeting certain threshold standards (Flora et al., 2025). Thus, insurers with better AI adoption disclosure are likely to demonstrate greater auditability, well-documented underwriting and claims processes, and more organizational governance-control changes disclosure. The positive transparency association is directionally consistent with accounting research linking clearer valuation and reporting practices to more reliable financial representation, although that literature also warns of manipulation and regulatory risk (Alsmadi & Alrawashdeh, 2025).

As the results of bootstrapped indirect-path estimation (with 5,000 samples) show, the paths relating AI adoption to financial transparency ($\beta = 0.21$, 95% CI [0.14, 0.29], $p = 0.002$) and organizational change ($\beta = 0.19$, 95% CI [0.11, 0.27], $p = 0.007$) via financial efficiency are statistically distinguishable from zero. Therefore, it appears that bootstrapped indirect path estimation is suitable for determining whether two regression paths are distinguishable from each other; however, confidence intervals still rely on resampling assumptions (Alfons et al., 2022; Tibbe & Montoya, 2022). However, no causation or mediation should be claimed here because the dependent variables are also based on disclosure data. The current model explains 64%, 61%, and 69% of the variance in the dependent variables (transparency, efficiency, and organizational change, respectively). Given that the model was built based on disclosure-coding procedures, these percentages indicate high explanatory power.

Given that the sample contains only insurers with sufficient AI disclosure, and the constructs are all based on related public documents coded similarly, some degree of co-disclosure may occur among the constructs, meaning that firms that disclose information about AI to a greater extent would disclose their financial transparency, efficiency, governance-control change practices, etc., in more detail as well. In other words, common method issues cannot be disregarded entirely in this case (Manata & Boster, 2024). To avoid 'too clean' interpretations, the analysis is considered disclosure-based and association-oriented, while potential sources of bias are highlighted in Table 6.

Table 3. Structural paths, bootstrapped indirect disclosure-based pathways, and model R^2 values linking AI adoption to organizational change

Expectation	Path	β / R^2	p	95% CI	Result
H1	AI adoption → Financial transparency	0.52	< 0.001	[0.43, 0.60]	Directional disclosure association only
H2	AI adoption → Operational efficiency	0.49	< 0.001	[0.40, 0.58]	Directional disclosure association only
H3	Financial transparency → Organizational change	0.41	0.003	[0.32, 0.50]	Directional disclosure association only
H4	Operational efficiency → Organizational change	0.38	0.012	[0.28, 0.47]	Directional disclosure association only
H5	AI → Transparency → Change	0.21	0.002	[0.14, 0.29]	Indirect disclosure pathway; not causal mediation
H6	AI → Efficiency → Change	0.19	0.007	[0.11, 0.27]	Indirect disclosure pathway; not causal mediation
Model	R^2: Financial transparency	0.64	–	–	Model-based disclosure variance
Model	R^2: Operational efficiency	0.61	–	–	Model-based disclosure variance
Model	R^2: Organizational change	0.69	–	–	Model-based disclosure variance

Table 4. Bayesian robustness estimates for direct and indirect paths in the insurance-company model

Path	Posterior mean	95% credible interval	P(> 0)
AI → Transparency	0.51	[0.42, 0.60]	0.99
AI → Efficiency	0.48	[0.39, 0.57]	0.99
Transparency → Change	0.40	[0.30, 0.50]	0.98
Efficiency → Change	0.37	[0.26, 0.47]	0.97
AI → Transparency → Change	0.20	[0.13, 0.28]	0.97
AI → Efficiency → Change	0.18	[0.10, 0.26]	0.96

The robustness of the parameters' stability in the SEM framework was confirmed using Bayesian SEM analysis. Bayesian Structural Equation Modeling is applicable to assess the stability of parameters in cases of latent variables modeling where sample size is modest, and parameter estimation depends on prior sensitivity (Liu et al., 2022). According to Table 4, posterior means resembled frequentist values; all 95% credible intervals excluded zero, and PSRF is about 1.00. Robust prior specification remains important when Bayesian structural models are used as validation layers (van Erp & Browne, 2021). The strongest posterior consistency was observed for the AI adoption → financial transparency and AI adoption → operational efficiency paths. These results

Table 5. Summary of directional-expectation results for AI adoption, transparency, efficiency, and organizational change

Expectation	Statement	Result
H1	AI adoption is positively associated with financial transparency	Aligned with disclosure-based association
H2	AI adoption is positively associated with operational efficiency	Aligned with disclosure-based association
H3	Financial transparency is positively associated with organizational change	Aligned with disclosure-based association
H4	Operational efficiency is positively associated with organizational change	Aligned with disclosure-based association
H5	Financial transparency forms an indirect disclosure-based AI-change pathway	Aligned with indirect disclosure pathway; not causal mediation
H6	Operational efficiency forms an indirect disclosure-based AI-change pathway	Aligned with indirect disclosure pathway; not causal mediation

Table 6. Sensitivity and bias checks used to avoid over-interpreting the uniformly positive disclosure paths

Issue	Design concern	Workbook check	Manuscript treatment
Disclosure bias	Public reports are not neutral windows into internal change	Disclosure_Bias_Flag and Disclosure_Bias_Note columns	Dedicated Discussion/Limitation paragraph added on selective disclosure and legitimacy signaling
Common-source bias	All constructs come from public disclosures and use related evidence logic	Document_Inventory separates document classes; Evidence_Quality marks triangulation	Triangulation explained across annual, audited, governance, ESG, investor, and regulatory materials; limitation retained
Verification gap	Numerical latent variables cannot be verified without an item-level matrix	Item_Coding_Annual and Coding_Examples provide the required structure	Item-level matrix and Appendix B coding examples added/referenced
Temporal ambiguity	2017–2023 appears like panel data, but the model is cross-sectional	Aggregation_Rule and formulas clarify firm-level aggregation	2017–2023 stated as observation window, not longitudinal SEM
Too-clean results	All paths are positive, and high R^2 may appear implausible if read as causal evidence	The manuscript treats the uniformly positive paths as disclosure-based co-disclosure patterns and avoids presenting them as causal operational effects	Results reframed as disclosure-based associations; R^2 and all-positive paths interpreted cautiously
Literature mismatch	Healthcare, renewable energy, project management, and communication studies are too central	Reference and literature audit prioritizes insurance, InsurTech, financial AI, GCC regulation, and disclosure research.	Broad cross-sector sources reduced; insurance, InsurTech, financial AI, GCC regulation, and disclosure studies prioritized.
Reporting-maturity risk	Positive SEM paths may reflect general disclosure sophistication rather than an internal AI-to-change mechanism	Construct-specific coding, document inventory, evidence-quality notes, and item-level scoring examples	Results and Discussion explicitly interpret paths as co-disclosure patterns and avoid causal mediation wording

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reinforce the stability of the reported associations in the sampled disclosure data, while remaining subject to co-disclosure, common-source, and public-document measurement limits.

Overall, the empirical results align with the six directional expectations, but this pattern is interpreted through the disclosure-design boundaries reported in Table 6. As summarized in Table 5, disclosed AI adoption is positively associated with disclosed financial transparency and operational efficiency, and both mechanisms are positively associated with disclosed organizational change. The indirect associations reported in Table 3 indicate that transparency and efficiency are modeled disclosure pathways through which AI adoption becomes externally observable as transformation in insurers' governance and operating routines. This interpretation remains disclosure-based and does not establish that AI internally caused transparency, efficiency, or organizational change. The differentiation above agrees with recommendations in structural equation modeling to separate between the model estimation and prediction or proving causality (Dash & Paul, 2021). Path coefficients and the amount of variance accounted for in each path were descriptively reported based on recommendations in structural equation modeling to ensure congruence between interpretation and the reason for modeling and data design (Hair & Alamer, 2022). Considering the nature of the sample and that all constructs have been drawn from disclosures, the all-positive findings can be interpreted as co-disclosure patterns.

4. DISCUSSION

Based on the present findings, AI adoption disclosed in GCC insurers is positively associated with disclosed organizational change through two mediation pathways: financial transparency and operational efficiency. While this finding corroborates literature on AI adoption in insurance stating that such a development occurs based on technological readiness, organizational capability, and environmental pressures (Gupta et al., 2022), it stands out in contrast with the literature on InsurTech, according to which technology adoption is mostly a digital transformation effort or a disruptive market change (Braun & Jia, 2025). The present results indicate that the latter can occur in organizations only where technology adoption is associated with transparent information, governance routines, and disclosure of workflow redesign.

This study's finding related to the financial transparency pathway corroborates the existing literature on explainable AI in insurance, stressing the importance of traceability, interpretability, and accountability (Owens et al., 2022). This study adds to the literature on financial transparency in the following way. By focusing on how financial transparency was made evident in public disclosures, it stresses four aspects: data lineage, audit trails, documentability quality, and consistency of reporting practices. As opposed to many works focusing on transparency in insurance, this study did not measure it as a technical or ethical feature of AI but as a disclosure outcome, which is critical because transparency language can be used even before it is embedded in decision-making systems.

The finding on the association between AI adoption and operational efficiency is in line with studies confirming the role of artificial intelligence in improving the efficiency of underwriting, pricing, claims management, and fraud detection (Dong & Quan, 2025). At the same time, it differs from previous research focused on automation speed and operational savings in the context of AI in insurance, which are sometimes accompanied by increased opacity and poor contestability. Therefore, operational efficiency should be interpreted as a form of controlled efficiency, as faster processes do not matter much unless there are proper documentation, human oversight, review, and escalation procedures in place.

As for the independent role of financial transparency and operational efficiency in organizational change, it aligns with the literature indicating that AI in insurance requires technical skills, capability of personnel, and organizational readiness for change (Acosta-Prado et al., 2024). What is different here is that the present study does not equate organizational change to a broad digital transformation claim but rather defines organizational change in terms of disclosed revisions of control routines, decision rights, performance indicators, staff training, and governance processes. Evidence from Iraqi commercial banks similarly indicates that digitally mediated communication can transmit the effects of electronic management practices to organizational performance, supporting the broader view that organizational change depends on communication routines as well as technology (Taqa, 2025).

It is reasonable to consider the indirect-path analysis presented above an important yet cautious contribution. Studies have examined separate issues such as AI adoption, service quality, or ecosystems of InsurTech in insurance (Patil et al., 2024; I. Sosa & S. Sosa, 2025). The present study makes an attempt to integrate the three areas by showing that in the context of public disclosure evidence, organizational change can be predicted based on two mediators between AI adoption and organizational change: financial transparency and operational efficiency. This does not mean that artificial intelligence internally caused these disclosure outcomes. Rather, it indicates that firms making stronger disclosures of AI adoption tend to make stronger disclosures of financial transparency and operational efficiency as well.

This disclosure-based study design has several limitations. First, disclosures of AI adoption, transparency, efficiency, and organizational change do not always reflect organizational reality. Public disclosures can serve many other purposes, such as legitimacy management, communication with investors, compliance with supervisory requirements, or selective reporting, which implies the existence of disclosure biases. Thus, more disclosure of one or both mediators may reflect only an organization's effort to create the appearance of greater AI adoption or deeper transformation rather than its reality.

Second, since all the constructs are measured based on public documents, there is the potential risk of common-source and common-coding biases. While the study tried to address the problem by triangulating different types of public documents (annual reports, financial statements, governance reports, sustainability reports, investor materials, and regulations) and separating items measuring AI adoption, transparency, efficiency, and organizational change, this approach could not eliminate the chance of bias completely. Therefore, the findings should be understood as disclosure associations.

Third, it is possible that the present findings can be explained by general reporting sophistication or maturity in disclosures. To be sure about the real nature of the disclosed pathway, future researchers will have to supplement the existing public-disclosure approach with process-level data, interviews, auditors' reports, supervisors' assessments, claims cycle times, error rates, and other data.

CONCLUSIONS

This study explores associations between disclosure of AI adoption, financial transparency, and organizational efficiency, as well as the relationship between the two mechanisms and disclosed organizational change. Positive correlations were found for AI adoption, each mechanism, and organizational change based on disclosure. However, these associations should be taken as indicating the presence of disclosure practices for related phenomena among organizations with adequate AI disclosure, but not as market-level evidence or causation for internal organizational changes. The major finding is that AI is considered organizationally relevant only if it has been integrated into auditable information systems, decision-making processes, controlled workflows, and corporate governance structures. Merely disclosing adoption does not suffice. Insurers should ensure that their use of AI has been linked to data lineage, auditing, exception handling, oversight, and human competencies. For supervisors, evaluating the quality of disclosures, documentation, model management, and governance practices would be paramount. Since the results only indicate correlations based on disclosures between 2017 and 2023, without using internal process data and a longitudinal panel, there remains uncertainty as to what extent such correlation may be due to reporting capabilities rather than actual internal change processes. Further study may employ interviews, claims processing cycle time measures, audit findings, error rates, dispute resolution evidence, and supervisory assessment. Future research should also examine how investors, policyholders, and other stakeholders select and interpret AI-related information, because digital information sources can influence communication agendas and information priorities (Ahmad et al., 2024).

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REFERENCES

1. Abu-AlSondos, I. A. (2025). Eliminating data silos with business intelligence: The role of organizational culture and leadership in Jordan's insurance sector. *Insurance Markets and Companies, 16*(2), 24-37. https://doi.org/10.21511/ins.16(2).2025.03
2. Acosta-Prado, J. C., Hernández-Cenzano, C. G., Villalta-Herrera, C. D., & Barahona-Silva, E. W. (2024). Three horizons of technical skills in artificial intelligence for the sustainability of insurance companies. *Administrative Sciences, 14*(9), 190. https://doi.org/10.3390/admsci14090190
3. Ahmad, A. K., Nahar, H. M., & Manajreh, M. M. N. (2024). Effect of social media on shaping the agenda of the communicator in the Jordanian TV channels. Middle East Journal of Communication Studies, 3(2), Article 3. https://doi.org/10.71220/2585-003-002-003
4. Ahmad, S., Karim, R., Sultana, N., & Lima, R. P. (2025). InsurTech: Digital transformation of the insurance industry. In M. Kour,S. Taneja, E. Özen; K. Sood, & S. Grima (Eds.), *Financial Landscape Transformation: Technological Disruptions* (pp. 287-299). Emerald Publishing Limited. https://doi.org/10.1108/978-1-83753-750-120251016
5. Ain, N. U., Vaia, G., DeLone, W. H., & Waheed, M. (2019). Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review. *Decision Support Systems, 125*, 113113. https://doi.org/10.1016/j.dss.2019.113113
6. Aldasoro, I., Gambacorta, L., Korinek, A., Shreeti, V., & Stein, M. (2025). Intelligent financial system: How AI is transforming finance. *Journal of Financial Stability, 81,* 101472. https://doi.org/10.1016/j.jfs.2025.101472
7. Alfiero, S., Battisti, E., & Hadjielias, E. (2022). Black box technology, usage-based insurance, and prediction of purchase behavior: Evidence from the auto insurance sector. *Technological Forecasting and Social Change, 183,* 121896. https://doi.org/10.1016/j.techfore.2022.121896
8. Alfons, A., Ateş, N. Y., & Groenen, P. J. F. (2022). A robust bootstrap test for mediation analysis. *Organizational Research Methods, 25*(3), 591-617. https://doi.org/10.1177/1094428121999096
9. Al-Muntasir, M. (2022). The phenomenon of information flow from traditional and new media about the Corona pandemic from the perspective of newly graduated media professionals in Yemen. *Middle East Journal of Communication Studies, 2*(2), Article 1. https://doi.org/10.71220/2585-002-002-005
10. Alshehadeh, A. R., Abu Nahleh, I. T., & AlZyoud, I. A. (2025). The impact of financial and non-financial information on investment decision-making in the Jordanian business environment. *Al-Zaytoonah University Journal of Business, 1*(1), 1-8. https://doi.org/10.15849/zjjb.v1i01.39
11. Alsmadi, A. A., & Alrawashdeh, N. (2025). The role and implications of finance revaluation: A comprehensive literature review. *Al-Zaytoonah University Journal of Business, 1*(1), 1-12. https://doi.org/10.15849/zjjb.v1i01.31
12. Bader, A., Qtaish, A., Odeh, K., & Sa'd, H. (2025). Artificial intelligence and big data in accounting: The case of commercial banks in Jordan. *Al-Zaytoonah University Journal of Business, 1*(3), 1-18. https://doi.org/10.15849/zjjb.v1i03.49
13. Bagherifam, N., Naghdi, S., Ahmadian, V., Fazlzadeh, A., & Baghalzadeh Shishehgarkhaneh, M. (2025). Digital regulatory governance: The role of RegTech and SupTech in transforming financial oversight and administrative capacity. *International Journal of Fi-*

nancial Studies, 13(4), 217. https://doi.org/10.3390/ijfs13040217

14. Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: A systematic literature review. *AI and Ethics, 5,* 3265-3279. https://doi.org/10.1007/s43681-024-00653-w

15. Bian, W., Ge, T., Ji, Y., & Wang, X. (2023). How is FinTech reshaping the traditional financial markets? New evidence from InsurTech and insurance sectors in China. *China Economic Review, 80,* 102004. https://doi.org/10.1016/j.chieco.2023.102004

16. Birkstedt, T., Minkkinen, M., Tandon, A., & Mäntymäki, M. (2023). AI governance: Themes, knowledge gaps and future agendas. *Internet Research, 33*(7), 133-167. https://doi.org/10.1108/INTR-01-2022-0042

17. Bonsón, E., Bednárová, M., & Perea, D. (2023). Disclosures about algorithmic decision making in the corporate reports of Western European companies. *International Journal of Accounting Information Systems, 48,* 100596. https://doi.org/10.1016/j.accinf.2022.100596

18. Braun, A., & Jia, R. (2025). InsurTech: Digital technologies in insurance. *The Geneva Papers on Risk and Insurance – Issues and Practice, 50,* 1-7. https://doi.org/10.1057/s41288-024-00344-x

19. Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management, 41*(2), 745-783. https://doi.org/10.1007/s10490-023-09871-y

20. Cofie, N., Braund, H., & Dalgarno, N. (2022). Eight ways to get a grip on intercoder reliability using qualitative-based measures. *Canadian Medical Education Journal, 13*(2), 73-76. https://doi.org/10.36834/cmej.72504

21. Cole, R. (2024). Inter-rater reliability methods in qualitative case study research. *Sociological Methods & Research, 53*(4), 1944-1975. https://doi.org/10.1177/00491241231156971

22. da Silva Tavares, E., Leardini, M., & de Paula Pessoa, M. S. (2025). How do the barriers that prevent or hinder the applicability of artificial intelligence impact its use in an insurance company? *Innovation & Management Review, 22*(1), 13-46. https://doi.org/10.1108/INMR-03-2022-0042

23. Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change, 173,* 121092. https://doi.org/10.1016/j.techfore.2021.121092

24. de Andrés-Sánchez, J., & Gené-Albesa, J. (2025). Drivers and necessary conditions for chatbot acceptance in the insurance industry: Analysis of policyholders' and professionals' perspectives. *Journal of Organizational and Electronic Commerce, 35*(3), 189-216. https://doi.org/10.1080/10919392.2024.2435118

25. Dong, P., & Quan, Z. (2025). Automated machine learning in insurance. *Insurance: Mathematics and Economics, 120,* 17-41. https://doi.org/10.1016/j.insmatheco.2024.10.002

26. Elgargouh, A., Chbihi Louhdi, M. R., Zemmouri, E. M., & Behja, H. (2024). Knowledge management for improved digital transformation in insurance companies: Systematic review and perspectives. *Informatics, 11*(3), 60. https://doi.org/10.3390/informatics11030060

27. Eti, S., Dinçer, H., Meral, H., Yüksel, S., & Gökalp, Y. (2024). Insurtech in Europe: Identifying the top investment priorities for driving innovation. *Financial Innovation, 10,* 38. https://doi.org/10.1186/s40854-023-00541-y

28. Flora, D. B., Crone, G., & Bell, S. M. (2025). Effect size interpretation in structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal, 32*(6), 1069-1076. https://doi.org/10.1080/10705511.2025.2459768

29. Gamerdinger, A., & Willers, J. O. (2025). Solving AI ethics? Hybrid expertise and professional power in EU ethics governance. *Journal of European Public Policy, 33*(7), 1813-1840. https://doi.org/10.1080/13501763.2025.2499113

30. Gupta, S., Ghardallou, W., Pandey, D. K., & Sahu, G. P. (2022). Artificial intelligence adoption in the insurance industry: Evidence using the technology-organization-environment framework. *Research in International Business and Finance, 63,* 101757. https://doi.org/10.1016/j.ribaf.2022.101757

31. Hair, J. F., & Alamer, A. (2022). Partial least squares structural equation modeling in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

32. Holland, C. P., & Kavuri, A. S. (2025). Insurtech strategies: A comparison of incumbent insurance firms with new entrants. *The Geneva Papers on Risk and Insurance – Issues and Practice, 50,* 78-105. https://doi.org/10.1057/s41288-024-00341-0

33. Ige-Gbadeyan, O. O., & Swanepoel, M. J. (2025). Exploring resilience: The impact of operational efficiency and financial health in South African non-life insurance companies. *Insurance Markets and Companies, 16*(1), 103-114. https://doi.org/10.21511/ins.16(1).2025.09

34. Khrais, L. T. (2025). Bridging gaps in InsurTech and e-commerce integration: Insights from Saudi Arabia. *Insurance Markets and Companies, 16*(1), 64-73. https://doi.org/10.21511/ins.16(1).2025.06

35. Lee, Y., & Yim, H. (2025). Trends in InsurTech development in Korea: A news media analysis of key technologies, players, and solutions. *Administrative Sciences, 15*(1), 25. https://doi.org/10.3390/admsci15010025

36. Liu, H., Qu, W., Zhang, Z., & Wu, H. (2022). A new Bayesian Structural Equation Modeling approach with priors on the covariance matrix parameter. *Journal*

of Behavioral Data Science, 2(2), 23-46. https://doi.org/10.35566/jbds/v2n2/p2

37. Ma, Y. L., & Ren, Y. (2023). InsurTech – Promise, threat or hype? Insights from stock market reaction to InsurTech innovation. *Pacific-Basin Finance Journal, 80,* 102059. https://doi.org/10.1016/j.pacfin.2023.102059

38. Manata, B., & Boster, F. J. (2024). Reconsidering the problem of common-method variance in organizational communication research. *Management Communication Quarterly, 38*(3), 677-697. https://doi.org/10.1177/08933189231226242

39. McNeish, D., & Wolf, M. G. (2023). Dynamic fit index cutoffs for Confirmatory Factor Analysis models. *Psychological Methods, 28*(1), 61-88. https://doi.org/10.1037/met0000425

40. Morshed, A. (2024a). Evaluating the effects of IFRS 9 on Jordanian banks' credit and financial metrics. *Banks and Bank Systems, 19*(4), 70-83. https://doi.org/10.21511/bbs.19(4).2024.06

41. Morshed, A. (2024b). Evaluating the influence of advanced analytics on client management systems in UAE telecom firms. *Innovative Marketing, 20*(4), 41-51. https://doi.org/10.21511/im.20(4).2024.04

42. Morshed, A. (2025). Navigating tradition and modernity: Digital accounting and financial integration in family-owned enterprises in the Arab Gulf. *Sustainable Futures, 9,* Article 100680. https://doi.org/10.1016/j.sftr.2025.100680

43. Morshed, A. (2026). *Data [Dataset]. Zenodo.* https://doi.org/10.5281/zenodo.20366451

44. Oreqat, A. (2021). The degree of satisfaction of Facebook users about its features, usage motives and achieved gratifications: An applied study on students of the Faculty of Mass Communication at the Middle East University. *Middle East Journal of Communication Studies, 1*(1), Article 1. https://doi.org/10.71220/2585-001-001-001

45. Owens, E., Sheehan, B., Mullins, M., Cunneen, M., Ressel, J., & Castignani, G. (2022). Explainable artificial intelligence (XAI) in insurance. *Risks, 10*(12), 230. https://doi.org/10.3390/risks10120230

46. Patil, K. P., Kulkarni, M. S., & Hudnurkar, M. (2024). Enhancing service quality in the insurance industry with AI-powered humanoid chatbots. *The TQM Journal, 37*(8), 2345-2371. https://doi.org/10.1108/TQM-11-2023-0354

47. Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2 – An improved criterion for assessing discriminant validity in structural equation modeling. *Industrial Management & Data Systems, 121*(12), 2637-2650. https://doi.org/10.1108/IMDS-02-2021-0082

48. Shaban, O. S., & Barakat, A. I. (2023). Evaluation of internal audit standards as a foundation for carrying out and promoting a wide variety of value-added tasks: Evidence from emerging market. *Journal of Risk and Financial Management, 16*(3), 185. https://doi.org/10.3390/jrfm16030185

49. Shaban, O. S., & Omoush, A. (2025). AI-driven financial transparency and corporate governance: Enhancing accounting practices with evidence from Jordan. *Sustainability, 17*(9), Article 3818. https://doi.org/10.3390/su17093818

50. Soleymanian, M., Weinberg, C. B., & Zhu, T. (2025). Insurtech, sensor data, and changes in customers' coverage choices: Evidence from usage-based automobile insurance. *Journal of Risk and Insurance, 92*(1), 227-256. https://doi.org/10.1111/jori.12490

51. Sosa, I., & Sosa, S. (2025). Building an InsurTech ecosystem within the insurance industry. *Risks, 13*(6), 108. https://doi.org/10.3390/risks13060108

52. Syed, A., Okegbola, O., & Akiotu, C. A. (2025). Utilising artificial intelligence and machine learning for regulatory compliance in financial institutions. In M. Albakri (Ed.), *Perspectives on Digital Transformation in Contemporary Business* (pp. 269-296). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-5966-2.ch010

53. Taqa, S. B. A. (2025). The mediating role of remote communication on the relationship between electronic human resource management practices and organizational performance in Iraqi commercial banks. *Middle East Journal of Communication Studies, 5*(1), Article 2. https://doi.org/10.71220/2585-005-001-001

54. Tibbe, T. D., & Montoya, A. K. (2022). Correcting the bias correction for the bootstrap confidence interval in mediation analysis. *Frontiers in Psychology, 13,* 810258. https://doi.org/10.3389/fpsyg.2022.810258

55. van Bekkum, M., Zuiderveen Borgesius, F., & Heskes, T. (2025). AI, insurance, discrimination and unfair differentiation: An overview and research agenda. *Law, Innovation and Technology, 17*(1), 177-204. https://doi.org/10.1080/17579961.2025.2469348

56. van Erp, S., & Browne, W. J. (2021). Bayesian multilevel structural equation modeling: An investigation into robust prior distributions for the doubly latent categorical model. *Structural Equation Modeling: A Multidisciplinary Journal, 28*(6), 875-893. https://doi.org/10.1080/10705511.2021.1915146

57. Vinora, A., Lloyds, E., Rajkumar, N. D., & Sivakarthi, G. (2024). Application of hyperautomation in insurance and retail industries. In R. K. Dhanaraj, M., Nalini, A. Daniel, A. K. Bashir, & B. Balusamy (Eds.), *Hyperautomation for Next-Generation Industries* (pp. 277-298). https://doi.org/10.1002/9781394186518.ch11

58. Vorobyev, I. (2024). Fraud risk assessment in car insurance using claims graph features in machine learning. *Expert Systems with Applications, 251,* 124109. https://doi.org/10.1016/j.eswa.2024.124109

59. Xie, S. (2024). Analyzing the influence of telematics-based pricing strategies on traditional rating factors in auto insurance rate regulation. *Mathematics, 12*(19),

3150. https://doi.org/10.3390/math12193150

60. Yaseen, H., & Al-Amarneh, A. (2025). Adoption of artificial intelligence-driven fraud detection in banking: The role of trust, transparency, and fairness perception in financial institutions in the United Arab Emirates and Qatar. *Journal of Risk and Financial Management, 18*(4), Article 217. https://doi.org/10.3390/jrfm18040217

61. Zaijuan, X., Ramayah, T., & Yubo, S. (2025). Determinants of generative AI adoption in insurance companies. *International Journal of Business and Society, 26*(1), 272-291. https://doi.org/10.33736/ijbs.9562.2025

62. Zarifis, A., Holland, C. P., & Milne, A. (2023). Evaluating the impact of AI on insurance: The four emerging AI- and data-driven business models. *Emerald Open Research, 1,* 15. https://doi.org/10.1108/EOR-01-2023-0001

63. Zhao, X., Zhai, G., Charles, V., Gherman, T., Lee, H., Pan, T., & Shang, Y. (2024). Enhancing enterprise investment efficiency through artificial intelligence: The role of accounting information transparency. *Socio-Economic Planning Sciences, 96,* 102092. https://doi.org/10.1016/j.seps.2024.102092

64. Zheng, Z., Tan, Q. L., Zheng, X., & Yang, Y. (2025). The dark side of AI in insurance: A systematic review of mechanisms linking AI design features to consumer harm. *Journal of Consumer Affairs, 59*(4). https://doi.org/10.1111/joca.70034

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APPENDIX A

The company list below provides a transparent company-level sample. The supplementary workbook retains the source type and inclusion-basis fields for each company.

Table A1. Company sample list

Company ID	Company name	Country
SA001	Bupa Arabia for Cooperative Insurance Company	Saudi Arabia
SA002	The Company for Cooperative Insurance (Tawuniya)	Saudi Arabia
SA003	Al Rajhi Company for Cooperative Insurance (Al Rajhi Takaful)	Saudi Arabia
SA004	The Mediterranean and Gulf Cooperative Insurance and Reinsurance Company (MEDGULF)	Saudi Arabia
SA005	Walaa Cooperative Insurance Company	Saudi Arabia
SA006	Gulf Insurance Group Saudi Arabia (GIG Saudi)	Saudi Arabia
SA007	Allianz Saudi Fransi Cooperative Insurance Company	Saudi Arabia
SA008	Malath Cooperative Insurance Company	Saudi Arabia
SA009	Aljazira Takaful Taawuni Company	Saudi Arabia
SA010	Arabian Shield Cooperative Insurance Company	Saudi Arabia
SA011	Saudi Arabian Cooperative Insurance Company (SAICO)	Saudi Arabia
SA012	Gulf Union Al Ahlia Cooperative Insurance Company	Saudi Arabia
SA013	Allied Cooperative Insurance Group (ACIG)	Saudi Arabia
SA014	Arabia Insurance Cooperative Company	Saudi Arabia
SA015	Al-Etihad Cooperative Insurance Company	Saudi Arabia
SA016	Al Sagr Cooperative Insurance Company	Saudi Arabia
SA017	United Cooperative Assurance Company (UCA)	Saudi Arabia
SA018	Saudi Reinsurance Company (Saudi Re)	Saudi Arabia
SA019	Salama Cooperative Insurance Company	Saudi Arabia
SA020	Wataniya Insurance Company	Saudi Arabia
SA021	Chubb Arabia Cooperative Insurance Company	Saudi Arabia
SA022	Buruj Cooperative Insurance Company	Saudi Arabia
SA023	Amana Cooperative Insurance Company	Saudi Arabia
SA024	Alinma Tokio Marine Company	Saudi Arabia
SA025	Liva Insurance Company	Saudi Arabia
SA026	Trade Union Cooperative Insurance Company	Saudi Arabia
SA027	Saudi Enaya Cooperative Insurance Company	Saudi Arabia
SA028	SABB Takaful Company	Saudi Arabia
SA029	Solidarity Saudi Takaful Company	Saudi Arabia
SA030	Saudi Indian Company for Cooperative Insurance (Wafa Insurance)	Saudi Arabia
UAE001	Abu Dhabi National Insurance Company (ADNIC)	UAE
UAE002	Emirates Insurance Company	UAE
UAE003	Al Ain Ahlia Insurance Company	UAE
UAE004	Dubai Insurance Company	UAE
UAE005	Al Dhafra Insurance Company	UAE
UAE006	Al Sagr National Insurance Company	UAE
UAE007	Dubai National Insurance & Reinsurance Company (DNIR)	UAE
UAE008	Ras Al Khaimah National Insurance Company	UAE
UAE009	United Fidelity Insurance Company	UAE
UAE010	Sukoon Insurance (formerly Oman Insurance Company)	UAE
UAE011	Al Wathba National Insurance Company	UAE
UAE012	Fujairah National Insurance Company	UAE
UAE013	Sharjah Insurance Company	UAE
UAE014	Orient Insurance Company	UAE
UAE015	Al Buhaira National Insurance Company	UAE
UAE016	Union Insurance Company	UAE
UAE017	Insurance House	UAE
UAE018	Hayah Insurance Company	UAE
UAE019	National Takaful Company (Watania)	UAE

Table A1 (cont.). Company sample list

Company ID	Company name	Country
UAE020	Abu Dhabi National Takaful Company	UAE
UAE021	Methaq Takaful Insurance Company	UAE
UAE022	Dubai Islamic Insurance and Reinsurance Company (AMAN)	UAE
UAE023	National General Insurance Company (NGI)	UAE
UAE024	Takaful Emarat Insurance	UAE
UAE025	Islamic Arab Insurance Company (SALAMA)	UAE
QA001	Qatar Insurance Company (QIC)	Qatar
QA002	Doha Insurance Group	Qatar
QA003	QLM Life & Medical Insurance Company	Qatar
QA004	Qatar General Insurance & Reinsurance Company	Qatar
QA005	Qatar Islamic Insurance Company	Qatar
QA006	Damaan Islamic Insurance Company (Beema)	Qatar
QA007	Al Khaleej Takaful Insurance Company	Qatar
QA008	SEIB Insurance and Reinsurance Company	Qatar
QA009	Sharq Insurance LLC	Qatar
QA010	Al Koot Insurance and Reinsurance Company	Qatar
QA011	Gulf Insurance Group Qatar (GIG Qatar)	Qatar
QA012	Medgulf Takaful Qatar	Qatar
QA013	Takaful International Company - Qatar/QFC branch	Qatar
QA014	Bahrain National Insurance Company - Qatar/QFC branch	Qatar
QA015	Zurich Insurance Company Ltd - Qatar/QFC branch	Qatar
QA016	Allianz Worldwide Care Ltd - Qatar/QFC branch	Qatar
QA017	American Life Insurance Company (MetLife/Alico Qatar)	Qatar
QA018	Cigna Insurance Middle East - Qatar	Qatar
QA019	Daman Health Insurance Qatar	Qatar
QA020	Q Life and Medical Insurance LLC	Qatar
KW001	Gulf Insurance Group (GIG Kuwait)	Kuwait
KW002	Kuwait Insurance Company	Kuwait
KW003	Al Ahleia Insurance Company	Kuwait
KW004	Warba Insurance and Reinsurance Company	Kuwait
KW005	Kuwait Reinsurance Company (Kuwait Re)	Kuwait
KW006	Bahrain Kuwait Insurance Company (BKIC)	Kuwait
KW007	Kuwait Qatar Insurance Company	Kuwait
KW008	Wethaq Takaful Insurance Company	Kuwait
KW009	First Takaful Insurance Company	Kuwait
KW010	Gulf Takaful Insurance Company (GIG Takaful)	Kuwait
KW011	Boubyan Takaful Insurance Company	Kuwait
KW012	KIB Takaful (formerly Ritaj Takaful)	Kuwait
KW013	Burgan Takaful Insurance Company	Kuwait
KW014	T’azur Takaful Insurance Company	Kuwait
KW015	Kuwait International Takaful Insurance Company	Kuwait
OM001	Liva Insurance Company	Oman
OM002	Dhofar Insurance Company	Oman
OM003	Oman Qatar Insurance Company	Oman
OM004	Al Madina Insurance / Al Madina Takaful	Oman
OM005	Takaful Oman Insurance Company	Oman
OM006	Oman United Insurance Company	Oman
OM007	Muscat Insurance Company	Oman
OM008	National Life & General Insurance Company	Oman
OM009	Al Ahlia Insurance Company	Oman
OM010	Arabia Falcon Insurance Company	Oman
OM011	Vision Insurance Company	Oman
OM012	Falcon Insurance Company	Oman
OM013	Sukoon Insurance	Oman
OM014	Orient Insurance Company	Oman

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Table A1 (cont.). Company sample list

Company ID	Company name	Country
OM015	Gulf Insurance Group - GIG Gulf Oman	Oman
BH001	Bahrain Kuwait Insurance Company (GIG Bahrain / BKIC)	Bahrain
BH002	Bahrain National Holding Company	Bahrain
BH003	Bahrain National Insurance Company	Bahrain
BH004	Bahrain National Life Assurance Company	Bahrain
BH005	Solidarity Bahrain	Bahrain
BH006	Takaful International Company	Bahrain
BH007	Arab Insurance Group (ARIG)	Bahrain
BH008	Trust Re	Bahrain
BH009	Gulf Union Insurance & Reinsurance Company	Bahrain
BH010	Medgulf Takaful	Bahrain
BH011	Hannover Retakaful	Bahrain
BH012	Life Insurance Corporation International - Bahrain branch	Bahrain
BH013	American Life Insurance Company (MetLife/Alico Bahrain)	Bahrain
BH014	The New India Assurance Company - Bahrain branch	Bahrain
BH015	Zurich Insurance Middle East / Zurich Bahrain	Bahrain

APPENDIX B

The examples below are taken from real company-level coding records in the supplementary workbook and show how textual evidence was mapped to item-level scores. Appendix B reports selected source-coded examples to illustrate the scoring logic, while the full company/source identifiers, document inventory, item-level coding trail, and aggregation formulas are available in the deposited Zenodo workbook. This avoids reproducing the full 840-row matrix in the manuscript while keeping the coding protocol auditable.

Table B1. Source-coded examples for converting textual disclosures into item scores

ID	Construct / item	Document / year	Score	Disclosure excerpt and scoring rationale
EX1	AI adoption: AI2_Claims_Triage	Annual report, 2023	3	Excerpt: Claims are triaged using AI-supported document review with human escalation. Rationale: Specific AI claims triage plus escalation/ control cue
EX2	AI adoption: AI3_Fraud_Analytics	Governance report, 2022	2	Excerpt: Machine-learning fraud alerts support investigation workflows. Rationale: Specific AI/ML fraud use is stated, but audit or review control is limited
EX3	Financial transparency: FT1_Audit_Trail	Audited financial statements, 2023	3	Excerpt: Pricing and reserving changes are linked to auditable data logs. Rationale: Traceability and auditability are explicit
EX4	Financial transparency: FT5_Consistency	Annual/governance reports, 2021	2	Excerpt: The same automation claim appears in the annual and governance reports. Rationale: Cross-document consistency exists, but implementation detail is moderate
EX5	Operational efficiency: OE2_Cycle_Time	Investor material, 2020	2	Excerpt: Digital claims review reduced manual handling time. Rationale: Efficiency is specific but not fully quantified or linked to controls
EX6	Operational efficiency: OE4_Workflow_ Standardization	Operations disclosure, 2023	3	Excerpt: A standardized claims workflow includes automated routing and exception review. Rationale: Workflow standardization and exception review are both visible
EX7	Organizational change: OC3_Decision_Rights	Governance report, 2023	3	Excerpt: Model outputs require review by underwriting supervisors before final approval. Rationale: Human oversight and decision rights are explicit
EX8	Organizational change: OC4_Staff_Reskilling	Sustainability report, 2022	2	Excerpt: Employees received digital analytics training. Rationale: Training is specific but not directly tied to governance routines