DIJEFA: Dinasti International Journal of Economics, Finance & Accounting
E-ISSN: 2721-303X
P-ISSN: 2721-3021
https://dinastipub.org/DIJEFA dinasti.info@gmail.com +62 811 7404 455
DOI: https://doi.org/10.38035/dijefa.v7i5.7500
https://creativecommons.org/licenses/by/4.0/
Received: 09 October 2026 | **Revised:** 30 October 2026 | **Accepted:** 09 November 2026

Data-Driven Underwriting Capability and Insurance Competitiveness: A Systematic Literature Review of Digital Analytics and Value-Creation Mechanisms

Chusnul Chotimah[1*], Ni Nyoman Sawitri[2], Vidiyana Rizal Putri[3]
[1]Universitas Bhayangkara Jaya, Jakarta, Indonesia, 20253051016@mhs.ubharajaya.ac.id
[2]Universitas Bhayangkara Jaya, Jakarta, Indonesia, -
[3]Universitas Bhayangkara Jaya, Jakarta, Indonesia, -

[*]Corresponding Author: 20253051016@mhs.ubharajaya.ac.id

Abstract: Digital analytics capabilities have the potential to help insurance companies process data into relevant information for underwriting decisions. However, the use of analytics technology is not synonymous with data-driven underwriting capabilities, and increased risk assessment accuracy does not in itself demonstrate increased firm competitiveness. This systematic literature review was designed to map empirical evidence on the relationship between digital capabilities, data-driven underwriting, and firm outcomes, while assessing the proximity of this evidence to the research idea of Digital Analytics Capability and Organization Capability–Data Driven Underwriting Capability–Insurance Competitiveness in general insurance companies in Indonesia. An initial search using Dimensions through three queries yielded 30 records each. After deduplication, 83 unique records were generated. Interim filtering grouped the records into core candidates, supporting articles, exclusion candidates, and review articles. Initial full-text validation was performed on five articles, while a targeted search identified several additional candidates that still require examination. Initial evidence indicates research on risk assessment analytics, information underwriting, decision automation, AI governance, and distribution digitalization; However, this evidence cannot be equated with direct testing of the overall mediation mechanism of data-driven underwriting capabilities toward competitiveness. Therefore, the purpose of this paper is to demonstrate a synthesis framework and evidence audit protocol.

Keywords: digital analytics capabilities, data-driven underwriting, insurance competitiveness, systematic literature review, general insurance.

INTRODUCTION

Underwriting is a core process in insurance companies because decisions regarding risk acceptance, risk classification, coverage terms, and premium determination affect portfolio quality and the company's technical output. Advances in data analytics, artificial intelligence, and digital decision-making systems are opening up opportunities to process larger amounts

and variations of data. However, the use of digital tools in a process is not enough to conclude that a company has established organizational capabilities. Capabilities require capabilities that can be used consistently, integrated with work processes, and directed toward organizational goals.

In this context, the review needs to distinguish at least four concepts. **First,** technology adoption refers to the use of digital tools or systems. **Second,** digital analytics capability refers to an organization's ability to access, integrate, analyze, interpret, and use data in decision-making. **Third,** data -driven underwriting capability (DDUC) refers to the ability to embed evidence and data analytics into underwriting routines. **Fourth,** firm competitiveness is a broader, firm-level outcome and cannot be reduced to a single technical measure such as model accuracy, premium growth, or claims ratio.

The first stage of this research identified related but distinctly focused literature. Amanda and Pradipta (2024), for example, examined a machine learning approach to risk-based premiums in insurance underwriting schemes in Indonesia. Liu, Chang, and Chen (2024) discussed underwriting information and profitability in motor vehicle physical damage insurance in Taiwan. Jansen, Nguyen, and Shams (2024) examined automated underwriting in the context of vehicle loans, so their findings can only be used as cross-industry analogies, not direct evidence from the insurance industry. Studies on digital transformation in insurance distribution also provide context for technology adoption, but do not necessarily explain underwriting mechanisms.

The synthesis problem that arises is that digital constructs, underwriting decisions, underwriting outcomes, financial outcomes, and competitiveness often exist at different levels of analysis. This distinction is maintained to avoid the risk of combining evidence that is not actually comparable. Therefore, each article is coded according to the insurance line context, level of analysis, constructs measured, methods, findings, limitations, and their level of proximity to the research idea of Digital Analytics Capability and Organizational Capability – Data-Driven Underwriting Capability – Insurance Competitiveness in general insurance companies in Indonesia.

This review is guided by three research questions. (1) How does empirical research conceptualize and measure digital analytics, underwriting data, and adjacent underwriting capabilities? (2) What evidence links digital capabilities or underwriting information to underwriting outcomes and firm results? (3) To what extent does verified evidence support the conceptual mechanism that positions DDUC as a connecting mechanism between organizational capabilities and insurer competitiveness?

The conceptual positions examined in the research idea on Digital Analytics Capability and Organizational Capability – Data Driven Underwriting Capability – Insurance Competitiveness in general insurance companies in Indonesia are Digital Analytics Capability (X1), Data Governance Capability (X2), Digital Infrastructure Capability (X3), and Organizational Learning Capability (X4) as candidate antecedents of DDUC (M), with Insurance Competitiveness (Y) as the outcome. These four antecedents are still conceptual choices that can be maintained, changed, or removed based on evidence synthesis and the appropriateness of construct boundaries. This article does not assume that DDUC mediation has been proven or that the novelty of the research idea on Digital Analytics Capability and Organizational Capability – Data Driven Underwriting Capability – Insurance Competitiveness in general insurance companies in Indonesia is strong enough.

METHODS

Review Design and Scope Boundaries

This study employed a systematic literature review design with narrative synthesis and framework-based coding. The substantive focus was on the relationship between digital

analytics capabilities, data-driven underwriting processes or capabilities, and firm-level outcomes in the insurance context. Cross-industry articles, distribution articles, AI governance studies, and pricing or risk prediction research can be maintained as adjacent evidence if their contribution function is explicitly stated. These articles are not reported as direct tests of the research ideational model of Digital Analytics Capability and Organizational Capability – Data-Driven Underwriting Capability – Insurance Competitiveness in general insurance companies in Indonesia.

Dimensions was used as the initial search database. Three sets of queries—Query A, Query B, and Query C—each selected 30 records in the compiled export. The complete query strings, search dates, applied filters, and export files were saved as audit attachments for replication.

Table 1. Search and deduplication summary

Stage	Records	Interpretation
Query A	30	Initial Dimensions retrieval; exact query/date to be inserted from search log
Query B	30	Initial Dimensions retrieval; exact query/date to be inserted from search log
Query C	30	Initial Dimensions retrieval; exact query/date to be inserted from search log
Total before deduplication	90	Raw retrieved records
Duplicates removed	7	DOI-first; normalized-title fallback
Unique records	83	Initial corpus, not final included sample

Source: Project search and deduplication summary; subject to audit.

Inclusion and Exclusion Criteria

The provisional inclusion criteria are: (1) articles relate to insurance, underwriting, risk selection, insurance pricing, risk analytics, or decision-making processes directly related to insurance company activities; (2) articles provide primary empirical evidence or findings that can be extracted transparently; (3) articles report relevant context, methods, constructs or variables, and findings; and (4) bibliographic identity can be traced. Review, bibliometric, or meta-analysis articles are not treated as primary empirical evidence, but are used for reference tracing and background mapping.

Provisional exclusion criteria included articles irrelevant to the research question, articles without extractable evidence, duplications, records whose identity could not be verified, and articles that only mentioned the terms digital or underwriting without substantive connection to the review focus. Final decisions were made after examining the full text, not just the title or abstract, to declare final exclusions if relevance was unclear.

Table 2. Categories from the Preliminary Second-Stage Screening

Category	Records	Treatment
Core candidates	3	Prioritize full-text review and direct evidence coding
Supporting studies	46	Retain when they support a defined synthesis theme
Potential exclusions	24	Confirm only after full-text check and record reason
Review articles	10	Background and citation chasing; separate from primary evidence
Total unique records	83	Categories sum to preliminary deduplicated corpus

Source: Document processing by the author

Bibliographic Duplication, Filtering, and Auditing

Deduplication was performed using DOI as the primary identifier. If a DOI was not available, titles were normalized to identify duplicate records. The initial process yielded 83

unique records from the 90 raw records. Subsequently, each record was assigned a stable ID and the status of title/abstract review, full-text review, inclusion decision, exclusion reason, DOI status, publisher metadata, and indexing verification were recorded. Therefore, the 83 represents the initial unique corpus, not the final number of articles.

Table 3. Research selection flow reporting framework

Flow Component	Amount	Notes That Must Be Recorded
Records identified from Dimensions	90	Query A = 30; Query B = 30; Query C = 30
Duplicates removed	7	Record the rules and deduplication log
Unique records screened	83	Initial count after deduplication
Records excluded at title/abstract stage	Not yet finalized	Content of the screening log
Full texts sought/retrieved	Not yet finalized	Note full texts that could not be obtained
Full texts excluded	Not yet finalized	Include reasons and number per reason
Studies included in final synthesis	Not yet finalized	Determined only after all criteria and audit are completed

Source: Author Management

Extra Procedures and Coding

Each study that passed full-text screening was extracted using a standard format. Extraction elements included author and year; title and journal; DOI; country and line of insurance; theory or perspective cited by authors; publication type; design, sample, and analysis method; definition and measurement of digital constructs; underwriting constructs; outcome variables; key findings; limitations stated by authors; limitations interpreted by reviewers; indexation status; and relevance to pathways X1/X2/X3/X4–M–Y.

Coding uses four categories. Direct evidence tests a data-driven underwriting construct or an equivalent construct and relevant company outcomes, ideally including indirect path testing. Near-direct evidence tests one part of a mechanism, such as underwriting information on profitability. Adjacent evidence includes risk analytics, pricing fairness, digital transformation, or AI adoption, which provide context but do not test the full model.

Table 4. Evidence proximity level coding framework

Level of Evidence	Operational Rules	Permissible Inferences	Project Candidate Examples
Direct	Measure DDUC/underwriting capability of similar type and test company outcomes; mediation tested when relevant.	Can support or refute pathway X1/X2/X3/X4–M–Y directly.	No confirmed study yet as full model testing within validated subset.
Almost direct	Test underwriting information or analytics and underwriting/financial outcomes, but not the full model.	Supports only part of the mechanism.	Liu et al. (2024); Amanda and Pradipta (2024), within respective contextual boundaries.
Adjacent	Examine AI classification, price fairness, digital transformation, distribution, or risk assessment without full	Provides context, candidate dimensions, or supporting factors; not full mediation	Choudhari and Jain (2026); Israni et al. (2026); Eckert et al. (2021); status of some candidates still
Exclusion	Does not meet relevance, evidence, or verification criteria	Not used to conclude construct	Record specific reasons for each excluded entry.

Source: Author's processing

Synthesis Strategy

The synthesis was conducted narratively, not meta-analytical, because the candidate papers differed in context, unit of analysis, variable definitions, designs, and types of outcomes. The synthesis was structured through: (1) mapping contexts and types of evidence; (2) comparing definitions and operationalizations of digital and underwriting constructs; (3) grouping results at the decision, portfolio, and firm levels; (4) assessing interconnectedness between constructs; (5) identifying evidence boundaries and research gaps; and (6) assessing the position of I4 based on fully verified evidence.

In the synthesis, prediction accuracy, risk classification quality, underwriting performance, profitability, premium growth, efficiency, and competitiveness are treated as distinct outcomes. The relationships among these outcomes are discussed as potential

mechanisms, but are not considered equivalent without explicit theoretical and measurement basis.

RESULTS AND DISCUSSION

The initial articles comprised 83 unique records. Preliminary screening identified three core candidates, 46 supporting articles, 24 exclusion candidates, and 10 review articles. These categories help guide work priorities, but cannot yet be considered the final number of studies, as some records still require full-text review and metadata verification. The supporting article category also does not necessarily mean that all of these articles will be cited as empirical evidence for each model pathway.

The third phase began full-text validation of five articles with different evidence functions. Holland and Kavuri (2025) compared the strategies of established and new insurance companies, including the use of AI, big data, and digital technologies. Ramachandaran et al. (2025) discussed the challenges of AI-based business intelligence systems in the Malaysian insurance industry, including data quality, legacy system integration, skills, and organizational culture. Eckert et al. (2021) examined the digital transformation of insurance sales in Germany, so its relevance to underwriting is indirect. Mullins et al. (2021) focused on ethical guidelines for AI and big data analytics in the European consumer insurance market. Ramezani et al. (2025) is a scoping review of AI applications in health insurance and not primary empirical research.

Table 5. Full text validation notes stage 3

Study	Context/Design	Main Relevance	Provisional Role and Inference Boundaries
Holland & Kavuri (2025)	Comparative case study of incumbent and new entrant companies	InsurTech strategies, AI, big data, and digital testing practices	Supporting evidence for digital strategies; not a direct quantitative test of DDUC or mediation.
Ramachandran et al. (2025)	Qualitative study of AI-based business intelligence systems in Malaysian insurance	Data quality, legacy system integration, skills, culture, and governance	Supports success factors/barriers; not a direct test of underwriting–competitiveness.
Eckert et al. (2021)	Survey of 671 insurance agents/intermediaries	Digital transformation in insurance sales	Adjacent distribution evidence; not underwriting-
Mullins et al. (2021)	Article on AI ethics guidelines and big data analytics in the European consumer insurance	Governance and ethics of AI/data use	Conceptual supporting evidence; not primary empirical study for X1/X2/X3/X4–M–Y
Ramezani et al. (2025)	Scoping review of AI applications in health	Mapping AI applications in health	Background and reference tracing; not primary

Source: Document Management

These five articles demonstrate that relevant evidence is scattered across digital strategy, data/AI governance, distribution, and AI applications in specific insurance lines. However, this subset does not yet provide a direct examination of the entire Digital Analytics Capability and Organizational Capability – Data-Driven Underwriting Capability – Insurance Competitiveness pathway. The statement is limited to the five articles reviewed, and cannot be generalized as evidence that such research does not exist.

Directed Search and Evidence Closest to the Path Digital Analytics Capability and Organizational Capability – Data Driven Underwriting Capability – Insurance Competitiveness

Step 4 expanded the search to articles more closely related to underwriting analytics and its outcomes. The candidates found were not at the same level of closeness. Amanda and Pradipta (2024) used a machine learning approach to classify risks and examine risk-based premiums in insurance underwriting schemes in Indonesia. The article provides contextual evidence on risk analytics in Indonesia, but its object was not directly the policy underwriting process in general insurance companies. Liu et al. (2024) is a closer candidate because it links

underwriting information and profitability in motor vehicle physical damage insurance in Taiwan.

Jansen et al. (2024) discuss automated underwriting in auto loans, not insurance. Therefore, the article can only serve as a cross-industry analogy for decision automation and should not be conflated with insurance evidence as if the context were the same. Choudhari and Jain (2026) examine machine learning for fair and explainable health insurance underwriting, while Israni et al. (2026) compare the performance and fairness of machine learning models for non-life insurance pricing. Both have the potential to support technical discussions of data-driven decisions, but do not, by themselves, test a company's competitiveness.

Table 6. Primary article candidates from stage 4 of the targeted search

Study/Candidate	Context and Focus	Potential Evidence Contribution	Status and Usage Boundaries
Amanda & Pradipta (2024)	Insurance guarantee scheme in Indonesia; machine learning for risk-based premiums.	Analytics and risk grouping, differences in life/non-life risk factors.	Candidate for direct/adjacent audit; not a DDUC insurer in policy underwriting.
Liu, Chang, & Chen (2024)	Motor vehicle physical damage insurance in Taiwan.	Underwriting information, risk standardization, and profitability.	Priority candidate; full-text audit and final metadata required.
Jansen, Nguyen, & Shams (2024)	Vehicle credit, not insurance industry.	Underwriting automation and credit/class outcomes.	Cross-industry analogy only; separate from insurance evidence.
Choudhari & Jain (2026)	Health insurance underwriting; machine learning, fairness, explainability.	Risk classification and fairness considerations.	Adjacent technical evidence; does not test company style.
Israni et al. (2026)	Non-life insurance pricing; comparison of GLM and machine learning models.	Trade-off between predictive accuracy and price fairness.	Adjacent technical evidence; ensure DOI and publisher metadata.
Boodhum & Jayabalan (2018)	Risk prediction in life insurance industry using supervised learning.	Foundational reference for predictive algorithm applications.	Older article; use for context/snowballing after audit.
Siregar et al. (2026)	Indonesian life insurance; AI-based verification, KYC, and risk assessment accuracy.	Potential link between AI verification capability and risk assessment.	Awaiting full-text validation to confirm empirical data and results are reported.
Uzbekistan proceedings candidate	Underwriting performance prediction using historical data 2017–2023.	Potential modeling of underwriting performance forecasting.	Check author identity, proceedings, DOI, and publication quality.
Indonesia candidate: Sharia insurance underwriting	Underwriting performance and premium income in Indonesian Sharia insurance context.	Local context of underwriting outcomes.	Digital analytics relevance unclear; check full text.
Risks (2025) candidate on algorithmic bias	Life/health underwriting, compliance risk, pricing, and ML models.	Potential forms of bias and algorithm governance.	Requires full-text audit, methodology, data, and metadata before use.

Source: Document Management

Based on table 6, the author obtained a map of the proximity of evidence to the research idea model on Digital Analytics Capability and Organizational Capability – Data Driven Underwriting Capability – Insurance Competitiveness in general insurance companies in Indonesia which is explained in the following table 7.

Table 7. Evidence Proximity Map with Digital Analytics Capability and Organizational Capability Models – Data Driven Underwriting Capability – Insurance Competitiveness

Level of Evidence	Operational Rules	Candidate Examples	Permissible Inferences
Direct	Measure data-based underwriting capability and company-level outcomes, and test relevant relationships.	No confirmed study yet testing the full model within validated subset.	Cannot yet state that DDUC mediation is supported.
Almost direct	Link underwriting information/analytics with underwriting or financial outcomes.	Liu et al. (2024); Amanda & Pradipta (2024), with contextual differences.	Supports part of the mechanism, not the entire model.
Adjacent	Examine AI, fairness, risk prediction, governance, or digitalization in related processes.	Choudhari & Jain (2026); Israni et al. (2026); Holland & Kavuri (2025); Ramachandran et al. (2025).	Supports dimension/context determination; not direct mediation evidence.
Cross-industry	Apply algorithmic underwriting in industries other than insurance.	Jansen et al. (2024), vehicle credit context.	Conceptual analogy only; should not be merged with insurance samples.
Review/Conceptual	Summarize literature or discuss governance principles without primary empirical	Ramezani et al. (2025); Mullins et al. (2021).	Background and reference tracing, not counted as primary empirical evidence.

Source: Document Management

Synthesis of Mediation Mechanisms and Gaps

Stage 5 focuses on the question of whether DDUC can be justified as a connecting mechanism between organizational capabilities and competitiveness. The synthesis needs to distinguish three groups of relationships. **First,** digital capabilities lead to DDUC: analytics, data governance, infrastructure, and organizational learning can be treated as candidate antecedents, but these relationships must be supported by definitions and measures that demonstrate organizational capabilities, not simply the presence of tools. **Second,** DDUC or underwriting information leads to outcomes: evidence on risk screening and profitability can support this part, but specific financial outcomes do not automatically equate to competitiveness. **Third,** digital capabilities lead to other mediators such as efficiency or service innovation: this evidence is relevant as a comparison mechanism, not as proof that DDUC is a mediator.

Table 8. Mediation evidence matrix (Stage 5)

Pathway	What it may show	What it does not show yet	Validation task
Digital capability → DDUC	Analytics, AI, governance, and infrastructure may enable data-intensive underwriting	That DDUC was measured as a distinct capability	Check construct definitions, indicators, causal direction
DDUC/underwriting information → firm outcome	Information and screening may relate to profitability or underwriting outcomes	That DDUC mediates digital analytics → competitiveness	Check outcome, model, temporal logic
Digital capability → alternative mediator → outcome	Digital adoption may relate to performance through efficiency/service innovation	That mediator is DDUC or outcome is competitiveness	Separate adjacent mediation from focal mediation
Digital analytics → DDUC → competitiveness in Indonesian general insurance	Would directly address I4	No direct test confirmed in validated subset	Continue search, citation tracing, full-text verification

Source: Synthesis of Stages 1–5; absence statement limited to validated subset

An Integrative Framework of Constructs and Implications for the Digital Analytics Capability and Organizational Capability Model – Data Driven Underwriting Capability – Insurance Competitiveness

The tentative synthesis framework positions four organizational capabilities as antecedents of DDUC candidates. Digital Analytics Capability (X1) relates to the ability to process and interpret data. Data Governance Capability (X2) encompasses data quality, access, security, accountability, and appropriate use. Digital Infrastructure Capability (X3) encompasses platforms and integrations that enable data flows. Organizational Learning Capability (X4) encompasses the ability to absorb feedback, update knowledge, and embed learning into routines. DDUC (M) is positioned as an organization's ability to repeatedly use data and analytics in the underwriting process. Insurance Competitiveness (Y) is positioned as a firm-level outcome that needs to be explicitly operationalized.

Table 9. Construct Synthesis and Construct Boundary Questions in the Digital Analytics Capability and Organizational Capability Model – Data Driven Underwriting Capability – Insurance Competitiveness

Construct/path	Provisional meaning	Question for synthesis	Status
Digital Analytics Capability (X1)	Ability to integrate, analyze, interpret, and use data	Capability or tool adoption?	Candidate antecedent
Data Governance Capability (X2)	Ability to ensure quality, access, accountability, security, appropriate use	Capability, controls, or compliance practice?	Candidate antecedent
Digital Infrastructure Capability (X3)	Platforms, integration, cloud, APIs, systems supporting data flow	Does it enable underwriting routines or general digitalization?	Candidate antecedent
Organizational Learning Capability (X4)	Ability to interpret analytics, share knowledge, update routines	Distinct from analytics and data-driven decision-making?	Candidate antecedent
DDUC (M)	Repeatable ability to embed data and analytics in underwriting	Distinct from performance, accuracy, or AI adoption?	Focal mediator; provisional
Insurance Competitiveness (Y)	Strategic ability to sustain favorable position	Direct measure or proxy such as profitability?	Outcome boundary required
X → M → Y	Indirect pathway through DDUC	Is indirect effect estimated with uncertainty intervals?	No direct test confirmed in subset

Source: Document Management

Discussion on New Position

Based on the validated subset and candidate search results, the novelty of the Digital Analytics Capability and Organizational Capability – Data-Driven Underwriting Capability – Insurance Competitiveness Model cannot yet be definitively assessed as strong, moderate, or weak. Available evidence indicates that machine learning for risk prediction, pricing, fairness, decision automation, AI governance, and digital transformation has been discussed in various contexts. Therefore, claims of novelty should not be based on general assertions that analytics technology has never been applied to underwriting.

A novelty that still deserves testing is the conceptual integration between organizational capability—not just technology adoption— data-driven underwriting capability as a mechanism distinct from technical outcomes, and competitiveness at the general insurance company level in Indonesia. The strength of this claim depends on whether the final study matrix shows that these constructs have not been integrated or tested in the same context and unit of analysis. If a direct study is found, the position of the Digital Analytics Capability – Data-Driven Underwriting Capability – Insurance Competitiveness Model needs to be sharpened through construct boundaries, mechanisms, the Indonesian context, or research design, rather than ignoring contrary evidence.

Three principles need to be maintained in the final revision. First, technology adoption should not be equated with organizational capability without evidence of routines and process integration. Second, predictive accuracy, underwriting quality, profitability, and competitiveness should be distinguished. Third, the absence of evidence in the examined subset should only be reported as a limitation of the validated corpus, not as a claim that the research does not exist.

CONCLUSION AND RECOMMENDATIONS

This article compiles the SLR and synthesis framework from Stages 1–5. The initial search yielded 90 raw records and 83 unique records after seven duplicates were removed. Interim filtering divided the records into three core candidates, 46 supporting articles, 24 exclusion candidates, and 10 review articles. Five articles formed the initial validation subset, while the directed search added candidates with varying degrees of proximity to the Digital Analytics Capability – Data-Driven Underwriting Capability – Insurance Competitiveness Model. These numbers and classifications remain preliminary.

The substantive conclusions that can be drawn at this point are limited: the literature reviewed covers some components of the mechanisms studied, but the validated evidence is insufficient to state that the entire digital capability → DDUC → competitiveness pathway has been tested or that DDUC mediation is proven. The contribution of the manuscript at this stage is the conceptual separation and auditable synthesis procedure.

Limitations

This paper has several limitations. First, the manuscript deliberately maintains a boundary between available results and those that remain to be verified. The initial corpus consists of 83 unique articles out of the initial 90. Second, the evidence reviewed is insufficient to conclude that Data-driven Underwriting Capability (DDUC) mediation has been proven or that the novelty of the model is Digital Analytics Capability and Organizational Capability – Data Driven Underwriting Capability – Insurance Competitiveness is definitely strong. Therefore, some tables still function as work matrices that must be completed.

Recommendations

Further research should expand the scope of research objects, increase sample size, use a longer observation period, and include other relevant variables to develop a more comprehensive research model.

Author Contribution

This research is expected to provide theoretical and practical contributions. Theoretical benefits relate to the development of strategic management studies on digital capabilities, data-driven underwriting capabilities, and company competitiveness. Practical benefits relate to the use of research findings as considerations in developing capabilities and formulating strategies for general insurance companies.

AI Use Statement

The author uses ChatGPT to help organize the literature review flow and draft the language. The author is responsible for checking primary sources, verifying metadata, confirming extraction results, interpreting evidence, and approving the final manuscript. Conform to journal policies and actual AI contributions.

REFERENCES

Amanda, C., & Pradipta, AD (2024). Risk-based premiums of insurance guarantee schemes: A machine-learning approach. Journal of Indonesian Economy and Business, 39(2), 121–142. https://doi.org/10.22146/jieb.v39i2.9323

Boodhun, N., & Jayabalan, M. (2018). Risk prediction in life insurance industry using supervised learning algorithms. Complex & Intelligent Systems, 4, 145–154. https://doi.org/10.1007/s40747-018-0072-1

Choudhari, S. M., & Jain, S. (2026). From bias to business insight: Evaluating machine learning approaches for fair and explainable health insurance underwriting. Humanities and Social Sciences Communications. https://doi.org/10.1057/s41599-026-07629-7

Eckert, C., Eckert, J., & Zitzmann, A. (2021). The status quo of digital transformation in insurance sales: An empirical analysis of the German insurance industry. Zeitschrift für die gesamte Versicherungswissenschaft, 110, 133–155. https://doi.org/10.1007/s12297-021-00507-y

Holland, J., & Kavuri, A. (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

Jansen, M., Nguyen, H. C., & Shams, A. (2024). Rise of the machines: The impact of automated underwriting. Management Science. https://doi.org/10.1287/mnsc.2024.4986

Liu, C.-T., Chang, C.-H., & Chen, H.H. (2024). Underwriting information and insurers' profitability: Evidence from automobile physical damage insurance in Taiwan. Pacific-Basin Finance Journal, 83, Article 102267. DOI and metadata must be checked against publisher record.

Mullins, M., Holland, C. P., & Cunneen, M. (2021). Creating ethics guidelines for artificial intelligence and big data analytics customers: The case of the European consumer insurance market. Patterns, 2(10), Article 100362. https://doi.org/10.1016/j.patter.2021.100362

Ramachandaran, S., Mahalley, Z., Nuraini, R., & Dhar, B. K. (2025). Exploring the challenges of AI-driven business intelligence systems in the Malaysian insurance industry. F1000Research, 14, Article 452. https://doi.org/10.12688/f1000research.163354.1

Ramezani, M., Bakhtiari, A., Mobinizadeh, M., et al. (2025). Artificial intelligence applications in health insurance: A scoping review. Cost Effectiveness and Resource Allocation, 23, Article 53. https://doi.org/10.1186/s12962-025-00640-w