“Impact of data warehousing adoption on underwriting and claims performance in Saudi insurance firms”

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IMPACT OF DATA WAREHOUSING ADOPTION ON UNDERWRITING AND CLAIMS PERFORMANCE IN SAUDI INSURANCE FIRMS

Abstract

Saudi insurers increasingly face demands to analyze huge quantities of underwriting and claims data, but disparate systems may decrease the precision of pricing and the speed of claim settlement, thereby reducing operational efficiency. The purpose of this study is to identify if data warehousing adoption could contribute positively to the underwriting and claims handling operations of insurance companies in Saudi Arabia. The study employed fixed-effect regressions to examine the relationship between data warehousing adoption and underwriting/claims handling operations of insurance companies based on a firm-year fixed-effect panel data set of 2015–2024, including information technology investment intensity interaction terms. The result of this study indicated that data warehousing adoption is positively related to underwriting/claims handling operations of insurance companies, where data warehousing adoption could contribute positively to reducing loss ratio by 4.8 percent ($\beta = -0.048$, $P < 0.01$) and combined ratio by 5.6 percent ($\beta = -0.056$, $P < 0.01$). Data warehousing adoption could also contribute positively to claims handling operations, where average claim settlement time could be reduced by 6.21 days ($\beta = -6.21$, $P < 0.05$). In addition, the data warehousing investment interaction term can provide an additional 3.2 percentage points of improvement ($\beta = -0.032$, $p < 0.05$), implying that data warehousing value can be enhanced by complementary investments in information technology capabilities. Explanatory powers of the model are considerable, with R-squared of 0.41-0.52 for different equations.

Keywords insurance, warehousing, underwriting, claims, performance, Saudi Arabia

JEL Classification G22, M15, C23, O33

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INTRODUCTION

The insurance business is becoming highly data-driven. Underwriting and pricing, claims management and adjudication, fraud detection, and regulatory compliance produce a massive amount of information that should facilitate well-informed and uniform decision-making. Nonetheless, it is common for insurance companies to maintain a legacy infrastructure and a set of separate databases designed for transaction handling rather than for integrated analytical purposes. If a customer and a risk portfolio are spread over a variety of systems with non-uniform terminology and structures, decision-makers may be forced to work with incomplete and untimely information. Information inefficiencies may be reflected in key performance metrics such as loss ratio, combined ratio, and claims adjudication speed.

Data warehousing is typically offered as a root solution because it integrates various data sources into a standardized database, which has higher data quality, allowing cross-functional analyses. However, the scientific problem with data warehousing is that the relationship between architecture and performance in insurance organizations has not been empirically ascertained. The differences that are observed

between those who adopt data warehousing solutions and those who do not may be attributed to efficiency drivers, but they could also be attributed to selection, such that firms that invest in better data infrastructure could be those that are inherently larger, better governed, or more advanced along digital lines.

The problem is particularly evident in rapidly modernizing markets like Saudi Arabia, in which insurance companies are challenged to increase underwriting discipline, minimize claims leakage, enhance levels of service, and meet changing supervisory requirements. Companies have varying levels of information technology preparedness and disclosures. Hence, rather than a scientific issue of whether technology is important in general, it is a matter of whether information architecture is related to efficiency in underwriting or claims handling after accounting for company differences.

1. LITERATURE REVIEW AND HYPOTHESES

The insurance sector across the globe is currently experiencing a technological revolution, owing to the development of data analysis and information technology. The insurance industry is quite competitive and is also experiencing increasing levels of regulation. In response to these challenges, data analytics is increasingly being used as a vital insurance company survival skill. Unfortunately, current information technology systems are not geared towards enabling advanced levels of analysis that are necessary for successful insurance company underwriting and claims handling. It is against this backdrop that a discussion on BI and data warehousing adoption in the industry is warranted.

Business Intelligence refers to the process of converting data into meaningful information to assist in decision-making in an organization. This is according to Mohammed et al. (2024) and Morshed (2025c). From a technological perspective, data warehousing is at the heart of business intelligence. It acts as a database where information from many sources is normally stored. These sources are mostly heterogeneous (Johnraja et al., 2024; Nalayini et al., 2024). In contrast, transaction-based systems that concentrate on processing data on a daily basis, data warehouse designs are specifically tailored for analysis, identification of patterns, and trending analysis. This approach helps organizations align data stored in various departments into a single platform, which helps enhance the quality, accuracy, and timeliness of data used for decision-making purposes. Business intelligence and data warehousing help organizations transition from intuition-based management decision-making approaches to data-based management practices and decision-making processes (Berkhout et al., 2024; Džanko et al., 2024). Over the last ten years, business intelligence and data warehousing have seen the integration of big data, AI, and cloud computing for data access and scalable storage solutions (Krishnan et al., 2024; Wijethilaka et al., 2025).

Empirical studies across various industry domains validate the argument that implementing Business Intelligence (BI) and Data Warehousing (DW) results in better organizational performance. It has been shown that organizations adopting BI technology performed better regarding decision-making accuracy, time, and costs (Arrassen et al., 2024; Prokop & Pergl, 2025). In the healthcare industry, data warehousing led to accuracy enhancement of reports, while control over operations was also improved (Avinash & Joseph, 2024). Again, in the banking industry, the implementation of business intelligence technology helped increase the profitability of the organization. This was achieved through more accurate forecasting and analysis of customer demand (Morshed & Khrais, 2025). However, it should also be borne in mind that for the success of business intelligence, organizational readiness, management support, and data management are essential. Without these, optimal results cannot be anticipated, even when using the latest technology in the business environment (Morshed, 2025a). Also, data warehousing maturity affects the success of business intelligence implementation (Jaradat et al., 2024; Sequeira et al., 2024).

The insurance sector provides a very applicable setting for the application of BI and DW due to the dependence on high volumes of different data. The process of underwriting and claims depends

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on the evaluation of different complex risk factors and the processing of high volumes of both structured and unstructured data. The integration of data through DW systems supports the identification of risk patterns, reduces errors in the process of underwriting, and improves the accuracy of the claims process (Hassan et al., 2024; Shah et al., 2024). It is observed that the application of BI technology in the insurance sector supports the activation of automation for different core business processes, combining the sectors of underwriting, administration, and claims in one analytical platform (Khayatbashi et al., 2025; Rachad et al., 2024). The combined and timely data obtained supports the improvement of decision-making and transparency, which affects the profitability of the sector (Adeniran et al., 2024; Nweke & Adelusi, 2025). In addition to that, the technology supports the acceleration of the claims process with integrity and reduced costs, along with the customers' satisfaction (Asawawibul et al., 2025).

The integration of Generative AI and Large Language Models has led to enhanced data analysis capabilities that have made it easier to query and analyze results (Salhab et al., 2025). Cloud solutions for data warehousing also offer insurers the advantages of scalability and elasticity to deal with larger data sets such as telematics and IoT data (Ionescu et al., 2025; Jreissat et al., 2024). This technology is beneficial and helps insurers not only gain easy access to data but also reduce the cost of data related to the environment (Chippagiri et al., 2025; Vijaya et al., 2025). However, the use of cloud and AI technology faces a number of issues related to data security and data ethics (Morshed, 2025d).

However, the potential of the implementation of BI and DW in the insurance sector may be affected by some technological and organizational issues. Legacy systems, dispersed data, and data quality may resist the integration of the system (Elgargouh et al., 2024; Pant, 2025). Additionally, resistance to change and a lack of analytical personnel can also reduce the success of technology investment efforts (Kusumawardhana et al., 2024). To ensure the success of BI, the greatest commitment and support must come from management and the culture of the organization, embracing data-based decision-making (Hasan et al., 2025). Companies with strongly developed DW typically have better data management and higher returns on their BI systems (Pattanaik et al., 2025).

Empirical studies carried out on developed and emerging markets illustrate the performance advantages that can be gained by integrating BI and DW. In the Kenyan market, the use of data-informed underwriting and risk management practices helped enhance the compliance and stability of the insurance organizations. In the Ethiopian market, the size of the organization and IT use exerts a positive impact on the profitability of the micro-insurance organizations (Ayele, 2025). In the developed markets, the use of BI and DW solutions helps enhance the transparency of the claim process together with the loss ratio (Horvey & Odei-Mensah, 2025; Ma & Jian, 2024).

However, several prominent gaps currently exist in the literature. Most existing literature is cross-sectional and descriptive, examining the perception of benefits of BI rather than measurable performance results (Raj et al., 2025; Tsiu et al., 2025). Longitudinal study data that explore the effects of DW adoption on firm results have not been used much. Existing literature also pays less attention to the infrastructural aspect of DW that specifically supports the use of business analysis (Macías & Borges, 2024). Geographically, literature has been dominated by Europe, the USA, and East Asian markets. Specifically, emerging markets have been overlooked. This is very true since the Middle East, for example, is continuing on a fast growth path, undergoing reforms, especially concerning the insurance sector (Al-Khazaleh et al., 2025). Specifically, within the Kingdom of Saudi Arabia, where the Vision 2030 initiative is undertaken, the insurance sector is undergoing heavy investment in data integration and analysis infrastructure (Abanumay & Alhumoud, 2025). Nonetheless, empirical studies examining the effects of these investments on the results of underwriting and benefits payments are still minimal.

Taken together, the literature provides a clear conceptual link between DW adoption and better performance results. The reliability of data necessarily results in better analytics, which positively affects the precision of the underwriting process and the efficiency of the processing of the claim, eventually positively influencing profitability. However,

it is surprising that, on the one hand, the consensus on the topic is not disputed, and on the other, there is little empirical support that attempts to measure the relationship.

In conclusion, the current state of knowledge through existing literature not only affirms the importance of BI and DW in facilitating the enhancement of the performance of data-intensive sectors, like the insurance industry, but also points out that the current state of knowledge is dominantly conceptual or country-focused, with very little literature on developing countries. Thus, it is important to systematically examine the adoption of DW technology by Saudi Arabia's insurance industry.

This paper aims to analyze the effects of data warehousing implementation on the performance of the underwriting and claims processes for insurance firms operating in the Kingdom of Saudi Arabia.

Drawing from the reviewed literature and identified gaps, the following hypotheses are proposed:

H1: Adoption of data warehousing has a significant negative effect on insurers' loss ratio.

H2: The adoption of data warehousing has a strong negative impact on the combined ratio of insurers, indicating improved operational efficiency.

H3: Data warehousing adoption has a significant negative effect on claim settlement time, indicating improved claims management efficiency.

H4: The positive effect of data warehousing adoption on performance is stronger for insurers with higher IT investment intensity.

2. METHODS

The following is the methodology used to analyze the impact of data warehousing on the underwriting and claims handling process in the insurance industry operating in the Kingdom of Saudi Arabia. It highlights the study design, data, variables, and analysis used for the objective of the proposed study. The proposed methodology will follow a quantitative explanatory paradigm using secondary panel data for a period of ten years, between 2015 and 2024.

To empirically examine these proposed links, the study employs a deductive methodological strategy informed by the literature on business intelligence and IS. By using panel data analysis, the study benefits from the higher statistical power of the methodology compared to cross-sectional analysis and allows for the control of differences between panels, which would not be possible with cross-sectional data. Additionally, panel analysis offers the advantage of exploiting the time variation between the cross-sections, compared to other data analysis approaches that only make use of cross-sections (Ghosh & Magotra, 2025).

The population of this research includes all insurance and reinsurance companies licensed by the Saudi Central Bank (SAMA) between 2015 and 2024. In the population, about twenty-five firms were selected according to the presence of data for at least five consecutive years. This sample includes both listed and private insurance firms that operate in different business segments, for example, medical, motor, property, and general insurance (Almoneef, 2025). Due to missing observations for some variables and years, the final estimation sample used for the main regressions is a balanced panel of 15 firms over 2015–2024.

Secondary data were obtained from various authoritative sources. Data were collected primarily from the annual Insurance Market reports issued by SAMA, which present a financial state of the insurers using variables such as premium earnings, incurred claims, loss ratios, and the combined ratio. Additional information on firm size, total assets, total liabilities, and IT costs was collected as secondary data. Finally, the information on the data warehousing and transformation projects was obtained from the management discussion and analysis, and the sustainability reports (Ryoji et al., 2025).

The process of data extraction included compiling numeric indicators annually from PDF files of Excel documents. This included setting up a panel

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data structure to handle specific company-year observations, which spanned from 2015 to 2024. Having a panel data structure enables one to examine the long-run impact of data warehousing on insurance (Oreqat, 2021).

The data included both the dependent and independent variables, which could be used for empirical analysis. The dependent variables included the processes involved in underwriting and claims. The loss ratio was used and referred to as the ratio of net claims incurred to the net premium earned, which explained the efficiency involved in the process of underwriting. The combination ratio, which was the total claim expenses and operating expenses divided by the net premium, explained the total operating efficiency. The average time involved in the process of claim settlement, measured in terms of days, explained the efficiency involved in the process of claim management (Morshed, 2025b).

The core independent variable was the adoption of data warehousing, which was represented using a binary indicator variable. This variable took the value of 1 for the years that a particular company was recognized to have undertaken the development of a data warehouse, data management platform, or similar technology, and 0 otherwise (Al-Muntasir, 2022). Some control variables were used, accounting for variables that could affect firm-level performance. These factors included the size of the company (represented by the natural logarithm of total assets), market share (represented by the premium of the particular firm divided by the total premium of the industry), IT investment intensity (represented by the IT expense divided by total operating expense), and leverage ratio (represented by the total liability divided by total assets) (Al-Daoud & Abu-AlSondos, 2025). Table 1 lists the variables, their respective definitions, measurements, and data sources.

Missing data were handled using linear interpolation, when applicable, and outliers were censored at the first and last percentiles. Monetary variables were also normalized using logarithms. The data were organized in long format, with indices for firms and years. It was also used for panel data analysis. Descriptive statistics, correlation matrices, and various tests of data suitability for regression analysis were performed for the data. These include tests for the presence of multicollinearity between the variables.

The econometric model estimated the effect of data warehousing on underwriting and claims performance while controlling for firm-specific characteristics and time effects. The baseline specification is represented as follows:

$$Y_{it} = \beta_0 + \beta_1 DW_{it} + \beta_2 ITINV_{it} + \beta_3 SIZE_{it} + \beta_4 MS_{it} + \beta_5 LEV_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \quad (1)$$

where Y_{it} denotes the performance indicator for firm i in year t (measured by loss ratio, combined ratio, or claim settlement time), DW_{it} represents data warehousing adoption, and μ_i and λ_t denote

Table 1. Variable definitions and measurements

Variable Type	Variable Name	Symbol	Definition / Measurement	Expected Effect	Source
Dependent Variables	Loss Ratio	LOSSR	Net claims incurred ÷ Net premiums earned	↓ with DW adoption	SAMA reports
	Combined Ratio	COMBR	(Claims + Operating expenses) ÷ Net premiums earned	↓ with DW adoption	SAMA reports
	Claim Settlement Time	CSTIME	Average number of days to settle claims (where available)	↓ with DW adoption	Company reports
Independent Variable	Data Warehousing Adoption	DW	1 if firm reports adoption of data warehouse/digital integration, 0 otherwise	–	Company reports / disclosures
Control Variables	Firm Size	SIZE	Natural logarithm of total assets	+	Tadawul financial statements
	Market Share	MS	Firm premiums / total market premiums	+	SAMA reports
	IT Investment Intensity	ITINV	IT expenditure / total operating expenses	+	Company financial statements
	Leverage Ratio	LEV	Total liabilities / total assets	–	Company financial statements

firm-specific and time-specific effects, respectively. The parameters β_1-β_5 represent the estimated coefficients for the independent and control variables, and ε_{it} is the error term.

Panel data regression analysis was used because it allows for the modeling of dynamics and differences. Two specifications of the model were estimated: the fixed effects model, which deals with time-invariant variables, and the random effects model, where the variables are assumed to vary randomly. The Hausman Specification Test was used for model selection. Robust standard errors were also calculated for the analysis of heteroscedasticity and correlation. For statistical analysis, the software used was R (plm) and Stata (xtreg) (Baltagi, 2024).

All data were obtained from publicly available, auditable secondary sources and compiled into a firm-year panel for 2015–2024. Underwriting performance measures and sector aggregates were extracted from official insurance-sector statistical releases issued by the Saudi Central Bank, while firm-level financial information and disclosures were collected from Tadawul filings and the annual reports of the sampled insurance firms; macroeconomic controls were sourced from widely used international databases. Data warehousing adoption (DW) was operationalized as a binary indicator based on explicit disclosure of data-warehouse (or equivalent) implementation in company reports. Before carrying out the analysis, the data was subject to a thorough cleaning process. The process involved a certain amount of limited interpolation for missing data, 1st and 99th percentile winsorization to minimize the impact of extreme data points, and standardization. The main innovation in the study is that it creates these publicly available data to investigate the relationship between the adoption of DW and insurance business performance. The final data set is available along with documentation in Zenodo (Zenodo, n.d.).

3. RESULTS AND DISCUSSION

In this section, we present our empirical results, with a focus on how the implementation of data warehousing (DW) influences underwriting and claims in the Saudi Arabian insurance industry, with our study period ranging from 2015 to 2024. To perform our analysis, a balanced panel dataset was constructed, with a sample of fifteen firms and ten years of consecutive data.. The choice of the panel regression model was supported by the Hausman test, where $\chi^2 = 15.24$, $p < .01$, indicating that individual variables are significantly associated with the other variables.

From Table 2, the average loss ratio for the sample is 0.68, indicating that insurers pay out, on average, 68% of their earned premiums on claims. The average combination ratio is 0.94, indicating a moderately efficient operation, while the average claim settlement period is 47.3 days. The binary variable for the adoption of DW has a mean of 0.42, indicating that 42% of the firm-year observations refer to insurers that reported the implementation of enterprise data warehouses or similar integration systems. The average size of the firms, represented by the natural log of total assets, is 8.76, while the average IT intensity, represented by the ratio of total operating costs to total operating costs, is 0.064. Market share and leverage are quite heterogeneous among firms, and, therefore, panel data analysis is applicable in this study (Dauda & Balogun, 2024).

The descriptive findings presented in Table 2 show that the average loss and combined ratios of adopt-

Table 2. Descriptive statistics of variables

Variable	Mean	Std. Dev.	Min	Max
Loss Ratio	0.68	0.13	0.40	1.01
Combined Ratio	0.94	0.10	0.71	1.20
Claim Settlement Time (days)	47.3	11.8	25.0	75.0
Data Warehousing Adoption (DW)	0.42	0.49	0.00	1.00
Firm Size (log assets)	8.76	0.79	7.05	10.10
Market Share (%)	5.84	4.92	0.75	18.60
IT Investment Intensity	0.064	0.028	0.02	0.12
Leverage Ratio	0.61	0.15	0.28	0.92

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ers of DW systems are lower than those of non-adopters, implying the potential efficiency benefit of data integration through IT. However, the large variability of IT intensity of investment among firms suggests that the level of technology capability could mitigate the relationship between DW implementation and organizational performance (Kapetanios et al., 2024).

To examine the initial correlations between the variables, the Pearson correlation coefficients were calculated. As shown in Table 3, the adoption of DW is negatively correlated with loss ratio ($r = -0.34$, $p < 0.01$), combined ratio ($r = -0.29$, $p < 0.01$), and claim settlement time ($r = -0.26$, $p < 0.05$). The negative correlations imply that the adopters of DW perform better on the underwriting and claim handling processes. Positive correlations between the adoption of DW, firm size ($r = 0.42$), and the intensity of IT investment ($r = 0.48$) imply that the bigger and more developed the IT insurers are, the higher the likelihood of adopting DW. Correlation coefficients do not exceed 0.75; hence, there are no multicollinearity concerns for the regression analysis.

The correlations identified in Table 3 offer initial support for the theoretical hypotheses of the study. The negative correlations between DW implementation and the ratios of performance identified that the use of integrated data systems could enhance the efficiency of the underwriting and claims processes. Correlations between DW adoption, organizational size, and IT intensity indicated the facilitating role of organizational capability.

To examine the first three hypotheses (*H1-H3*), fixed-effect regression analysis was employed. The findings, shown in Table 4, indicate that the adoption of the DW system statistically significantly affects the three performance measures negatively (Ahmad et al., 2023). That is, the average loss ratio is reduced by 4.8% ($\beta = -0.048$, $p < 0.01$), the average combined ratio is reduced by 5.6% ($\beta = -0.056$, $p < 0.01$), and the average number of days for claim payment is reduced by about 6.2 days ($\beta = -6.21$, $p < 0.05$) for the adopters of the DW system compared to the non-adopters.

The results, shown in Table 4, validate the hypotheses *H1, H2,* and *H3*. The negative significant coefficients indicate that the adoption of DW technology improves the processes involved in underwriting and claims. This result supports the basic

Table 3. Pearson correlation matrix of key variables

Variable	1	2	3	4	5	6	7	8
1. Loss Ratio	1.00							
2. Combined Ratio	.73**	1.00						
3. Claim Settlement Time	.56**	.48**	1.00					
4. DW Adoption	–.34**	–.29**	–.26*	1.00				
5. Firm Size	–.18	–.20	–.10	.42**	1.00			
6. Market Share	–.22*	–.19	–.11	.37**	.46**	1.00		
7. IT Investment Intensity	–.28**	–.31**	–.20*	.48**	.35**	.33**	1.00	
8. Leverage Ratio	.41**	.39**	.28**	–.21*	–.26**	–.19	–.17	1.00

Note: ** p < .01; * p < .05.

Table 4. Regression results (fixed effects model)

Variable	Loss Ratio (β)	Combined Ratio (β)	Claim Settlement Time (β)
Data Warehousing Adoption	–0.048***	–0.056***	–6.21**
Firm Size	–0.012	–0.009	–0.82
Market Share	–0.006**	–0.004*	–0.47
IT Investment Intensity	–0.217**	–0.245**	–3.14*
Leverage Ratio	0.089***	0.072**	2.56*
Constant	0.713***	0.864***	57.92***
Adjusted R^2	0.44	0.47	0.41
F-statistic	13.22***	15.87***	11.63***

Note: *** p < .01; ** p < .05; * p < .10.

notion that the integration of data results in better decision-making and optimization for these processes (Taqa, 2025). IT intensity and market share also have negative effects on the indicators of performance, suggesting that increased spending on technology and improved market positioning positively affect efficiency. However, the leverage ratio positively affects the loss ratio and the combination ratio, indicating that increasing leverage can negatively affect profitability (Sghaier, 2025).

To examine the moderating effect of IT investment intensity (*H4*), interaction variables of DW adoption with IT investment were introduced into the regression analysis. The results, shown in Table 5, reveal that the coefficient of the interaction variable is negative and significant for all models, suggesting that the marginal effect of DW adoption is larger for entities that invest more in IT.

The results presented in Table 5 provide evidence to support H4, which means that as the IT intensity of investment increases, DW implementation benefits also increase. This result makes it clear that it is not possible to gain the benefits of data integration, including redundancy elimination, without help from other technological investments to effectively gain from DW. This can be explained only in terms of the Resource-Based View Theory (Seshagiri & Prema, 2025). Taken together, the data in Tables 2 through 5 verify that all four hypotheses are true. DW helps enhance the accuracy of underwriting and the efficiency of the claims process, and IT investment helps augment these benefits. This is consistent with previous evidence that the use of integrated data technologies improves decision-making and risk analysis. Table 6 displays the hypotheses and results.

All four hypotheses from Table 6 are significant. This indicates that increasing IT investment intensity contributes to the data warehousing process (DW) in minimizing loss ratios and combined ratios and in fast-tracking claims processing. In general, the data warehousing process (DW) helps the Saudi Arabian insurance sector to achieve effective underwriting and claims administration.

The study offers concrete evidence that a data warehousing (DW) system has a beneficial effect on the underwriting and claim payment processes within Saudi Arabia's insurance industry. The leading metrics show that there are significant improvements in the following areas: a 4.8% reduction in the loss ratio, a 5.6% reduction in the combined ratio, and a reduction of 6.2 days in the time to pay claims. This supports the assumption that the use of various data technologies improves the decision-making processes of the organizations (Mohammed et al., 2024; Berkhout et al., 2024). Contrary to previous research on the matter, the current study has a positive and measurable outcome and supports the views of Arrassen et al. (2024)

Table 5. Moderating effect of IT investment

Variable	Loss Ratio (β)	Combined Ratio (β)	Claim Settlement Time (β)
Data Warehousing Adoption	−0.036**	−0.041**	−4.21*
IT Investment Intensity	−0.174**	−0.192**	−2.67*
DW × IT Investment	−0.032**	−0.028**	−1.95*
Firm Controls	Included	Included	Included
Adjusted R^2	0.49	0.52	0.45

Note: ** p < .05; * p < .10.

Table 6. Summary of hypotheses testing results

Hypothesis	Statement	Supported	Evidence
H1	Data warehousing adoption has a significant negative effect on the insurers' loss ratio.	Yes	β = −0.048, p < .01 (Table 4)
H2	Data warehousing adoption has a significant negative effect on insurers' combined ratio.	Yes	β = −0.056, p < .01 (Table 4)
H3	Data warehousing adoption has a significant negative effect on claim settlement time.	Yes	β = −6.21, p < .05 (Table 4)
H4	The positive effect of DW adoption on performance is stronger for firms with higher IT investment intensity.	Yes	β = −0.032, p < .05 (Table 5)

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and Prokop and Pergl (2025) on the beneficial effect of a DW system combined with business intelligence on the cost effectiveness of the underwriting and claim cost processes. The assumption that data integration leads to a reduction in claim management time due to the elimination of repetitive processes (Hassan et al., 2024; Shah et al., 2024) is validated and used for the first time on the conservative insurance market of Saudi Arabia. The moderating variable of IT investment intensity syncs with previous assertions that technological capability enhances the strength of the DW adoption relationship (Jaradat et al., 2024; Morshed, 2025a). Companies that invested heavily in IT infrastructure realized higher gains in efficiency, which echoes the RBV that digital assets can leverage organizational capability (Seshagiri & Prema, 2025).

Some of the findings align with or contradict previous studies that had inconsistent results for DW because of the existing systems and resistance to change (Elgargouh et al., 2024). The positive results of this study indicate that the barriers faced by organizations could have been lowered by national digital efforts, including the Saudi Vision 2030 initiative. Consequently, the results of this study fill the existing gap in the literature since they show that the adoption of DW leads to specific benefits.

CONCLUSIONS

The aim of this empirical study was the evaluation of the influence of data warehousing (DW) implementation on the level of underwriting and claims processing effectiveness among insurance industry players operating in the Kingdom of Saudi Arabia. The analysis used fixed effects regression on panel data covering the period 2015–2024.

The findings reinforced and elaborated on the initial findings. They reinforced the initial findings since they provided further evidence of the positive impact of DW technology on performance outcomes. Firms that adopted DW technology experienced positive outcomes on a number of metrics, including loss ratios, combined loss ratios, and the time taken to settle claims. The findings provided empirical evidence to support the assumption that data integration platforms can improve the precision of the findings and provide consistency to the results.. It was also revealed in the study how IT intensity acts as a moderating variable and how DW technology is more efficient when combined with higher technology capabilities.

Based on these findings, several conclusions can be made. Firstly, it is clear that implementing data warehousing is not just about implementing a new technology, it is also about enhancing the integrity of the data within a business entity. Secondly, it is evident that technological readiness is a fundamental factor that determines how these benefits are going to be achieved in the real world. In addition, in the future, further research could be carried out on data warehousing, for example, by extending the time scale of the study and adding more factors such as customer satisfaction and fraud detection.

AUTHOR CONTRIBUTIONS

Conceptualization: Ahmad Harasis.
Data curation: Ahmad Harasis.
Formal analysis: Ahmad Harasis.
Funding acquisition: Ahmad Harasis.
Investigation: Ahmad Harasis.
Methodology: Ahmad Harasis.
Project administration: Ahmad Harasis.
Resources: Ahmad Harasis.

Software: Ahmad Harasis.
Validation: Ahmad Harasis.
Visualization: Ahmad Harasis.
Writing – original draft: Ahmad Harasis.
Writing – review & editing: Ahmad Harasis.

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APPENDIX A

Table A1. Sample insurance and reinsurance firms (n = 25)

No.	Company
1	Al-Ahlia Insurance Co.
2	Alahli Takaful Co.
3	Al Alamiya for Cooperative Insurance Co.
4	Alinma Tokio Marine Co.
5	Al-Etihad Cooperative Insurance Co.
6	Aljazira Takaful Taawuni Co.
7	Allianz Saudi Fransi Cooperative Insurance Co.
8	Al-Rajhi Company for Cooperative Insurance
9	Amana Cooperative Insurance Co.
10	Arabia Insurance Cooperative Co.
11	Arabian Shield Cooperative Insurance Co.
12	AXA Cooperative Insurance
13	Bupa Arabia
14	Buruj Cooperative Insurance Co.
15	CHUBB Arabia Cooperative Insurance Co.
16	Gulf General Cooperative Insurance Co.
17	Gulf Union Cooperative Insurance Co.
18	Malath Co-operative Insurance
19	Salama Cooperative Insurance Co.
20	Saudi Re for Cooperative Reinsurance Co.
21	Saudi Arabian Cooperative Insurance Co. (SAICO)
22	Saudi Enaya Cooperative Insurance Co.
23	Saudi Indian Company for Cooperative Insurance
24	Solidarity Takaful
25	The Company for Cooperative Insurance (Tawuniya)