Evaluating the Impact of Business Intelligence on Enhancing Innovation in the Insurance Industry Considering the Role of Network Learning

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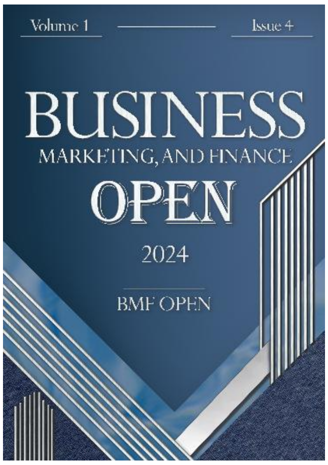

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Abstract: In today's competitive business world, Business Intelligence (BI) serves as a key tool for data extraction and analysis, playing a crucial role in enhancing organizational innovation. This study aims to evaluate the impact of Business Intelligence on improving innovation in the insurance industry, considering the role of network learning. The research method is descriptive and survey-based. The statistical population consists of managers from various departments within the insurance industry. Data collection was conducted through field research using a questionnaire, employing a convenience sampling method. Structural equation modeling (SEM) with the partial least squares (PLS) approach was used for data analysis, utilizing the SMART PLS3 software. The research findings indicate that Business Intelligence has a significant positive effect on innovation, and network learning acts as a mediating factor that strengthens this effect. Additionally, the results suggest that innovation directly and indirectly influences organizational performance, and organizations that leverage Business Intelligence capabilities benefit from greater innovative advantages. The study's recommendations include investing in Business Intelligence systems, promoting a data-driven culture, developing network learning, integrating BI with modern technologies (such as artificial intelligence and machine learning), and optimizing innovation strategies. This research can assist organizations in making better strategic decisions and enhancing their competitive advantage.

Keywords: Business Intelligence, Innovation Enhancement, Network Learning, Insurance Industry

1. Introduction

In today's innovation-driven environment, shaped by competition and globalization, a shared perspective on innovation has gained prominence. Consequently, both small and large enterprises have begun to collaborate in search of additional knowledge and resources that can facilitate continuous innovation and provide them with a competitive advantage [1]. Furthermore, research highlights the crucial role of innovation in achieving competitive advantage, assisting organizations in adapting to environmental fluctuations. Therefore, innovation is considered a key factor in long-term success, particularly in dynamic markets [2].

One of the most significant types of intelligence in the business environment, especially for senior organizational managers, is Business Intelligence (BI). Business Intelligence is a broad concept that encompasses the strategic direction of an entire organization. It involves acquiring, managing, and analyzing vast amounts of data related to partners, products, services, customers, suppliers, activities, and interactions among them [3, 4]. In other words, Business Intelligence is a systematic and structured process through which an organization gathers information from internal and external sources relevant to its activities and decision-making processes, analyzes it, and disseminates it. Business Intelligence is a comprehensive concept that enables the entire organization to utilize the provided information systems in the most effective way, aiming to obtain timely and high-quality data for decision-making, ultimately leading to competitive advantages [5].

This concept must be supported by senior organizational managers and developed throughout the organization. Given the rapid changes in the business environment and the increasing complexity of business processes, it has become increasingly challenging for managers to gain a comprehensive understanding of their business landscape. Factors such as globalization, deregulation, mergers and acquisitions, competition, and technological innovation have compelled companies to reconsider their business strategies [6]. In response, many large companies have turned to Business Intelligence as a means to understand and control business processes, thereby achieving competitive advantage. Business Intelligence improves business performance by significantly aiding executive decision-makers, enabling them to access actionable insights [3].

One of the fundamental principles of establishing an innovative environment is market awareness and understanding the broad range of potential opportunities, as well as recognizing the internal strengths and weaknesses of an organization. Business Intelligence and Competitive Intelligence, with their extensive capabilities, provide organizations with valuable information in these areas. Moreover, an organization's competitiveness is another crucial factor that plays a significant role in fostering an innovative environment. In fact, it can be argued that an organization's innovation is meaningless without its competitiveness. With the shortening life cycles of products and the technologies utilized in them, innovation has become increasingly important in business. Organizations must continuously innovate their processes, products, and services. Since innovation requires the generation of new ideas, organizations must actively explore and embrace novel thoughts and concepts. This pursuit of innovation should not be limited to the internal environment of organizations; rather, they should allow external ideas and insights to enter the organization—a concept known as Open Innovation [7-9].

Given the significance of this subject, the present study aims to examine the impact of Business Intelligence capabilities on organizational innovation, considering the mediating role of network learning and organizational performance. In this regard, the use of quantitative methods and structural equation modeling can provide a more precise understanding of the relationships between these variables, assisting organizations in developing data-driven and innovative strategies.

2. Methodology

The present study is classified as an applied research based on its objective and is considered a survey research in terms of data collection. The research structure is designed based on Structural Equation Modeling (SEM). Therefore, the Partial Least Squares (PLS) method was used for data analysis. This method was selected for two primary reasons: first, it does not rely on assumptions such as the normal distribution of observed indicators or large sample sizes; and second, according to Chin (1998), this method is used for predictive purposes and to explore potential relationships.

Considering maximum variance and a 5% error level, a total of 380 participants were selected using convenience sampling. Additionally, to increase the response rate and facilitate the research process, more than 400 electronic questionnaires were distributed. Out of these, 380 consumers of insurance industry services completed the questionnaire, and this number was used as the basis for hypothesis testing and analysis.

Furthermore, to assess the reliability of the questionnaire, Cronbach's alpha and composite reliability (CR) were employed. The reliability results for each variable indicate that all values exceeded 0.70, which signifies an acceptable level of reliability.

To evaluate the validity, convergent validity was assessed. Table 2 presents the findings related to convergent validity. The results indicate that the Average Variance Extracted (AVE) for the latent variables in the model was greater than 0.50. Therefore, it can be concluded that the convergent validity of the measurement models is satisfactory.

3. Findings

In this study, six main variables were selected for examination based on a conceptual model. Describing these variables is crucial because the results of hypothesis testing are derived from the data and indicators of these variables. The research data have an interval scale. To describe the research variables, central tendency and dispersion indicators were used, as discussed below.

Given that the five-point Likert scale was chosen for the questionnaire items, the respondents' scores were analyzed to determine whether the mean responses significantly differ from 3 (the midpoint of the Likert scale). If the mean is less than 3, it indicates an unfavorable status for the studied population concerning that indicator. For reverse-coded variables, the interpretation is reversed. Additionally, the absolute values of skewness and kurtosis coefficients indicate the deviation and symmetry of the sample distribution compared to a normal distribution. If these values fall within the range of -1 to 1, the distribution is considered normal and does not show significant deviation.

Table 1. Descriptive Statistics for Research Variables

Main Factor	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Causal Factors	4.45	0.713	0.509	-1.368	1.992
Contextual Factors	4.15	0.636	0.404	-1.153	1.553
Intervening Factors	4.06	0.668	0.447	-0.632	1.159
Strategies	3.86	0.744	0.553	0.961	1.933
Outcomes	3.84	0.791	0.626	-0.651	0.296

As shown in Table 1, all variables are in a favorable state.

The Partial Least Squares (PLS) method was used for data analysis. This method was chosen because, first, it does not depend on assumptions such as the normal distribution of observed indicators or a large sample size. Second, it is commonly used for predictive purposes and exploring potential relationships. Unlike covariance-based methods, which attempt to fit the data to a theoretical model, the PLS approach uncovers theories hidden within the data.

The research findings are categorized into two main sections: the first section focuses on validity and reliability of the constructs and indicators. In PLS analysis, two main tools, Average Variance Extracted (AVE) and Composite Reliability (CR), are used to assess construct reliability. Given that Cronbach's alpha provides a more stringent estimate of internal reliability, PLS path models typically rely on composite reliability as a more suitable measure. Regardless of the specific reliability coefficient used, Cronbach's alpha must exceed 0.70.

Table 2. Construct Validity and Reliability Assessment

Variable	Cronbach's Alpha	AVE	CR	Rho
Causal Factors	0.750	0.600	0.833	0.751
Contextual Factors	0.735	0.687	0.825	0.745
Intervening Factors	0.769	0.651	0.828	0.769
Strategies	0.793	0.678	0.743	0.731
Outcomes	0.774	0.659	0.832	0.778
Core Phenomenon	0.731	0.682	0.822	0.741

Additionally, as shown in Table 2, all CR values exceed 0.70, and all AVE values exceed 0.60. This confirms construct reliability and validity.

The coefficient of determination (R^2) measures the proportion of variance in an endogenous variable explained by the exogenous variables. The threshold values for this coefficient are as follows: R^2 greater than 0.670 is considered strong, values greater than 0.333 and up to 0.670 are considered moderate, and values less than 0.190 are considered weak. Essentially, the R^2 coefficient indicates the extent to which the independent variables account for variations in the dependent variable. Based on the computed values, structural validity and reliability of the model are confirmed.

Table 3 presents both correlation coefficients and an assessment of discriminant validity. According to this criterion, the variance of each latent variable should be greater for its own indicators than for other indicators. To determine this, the square root of the AVE for each latent variable is first calculated and then compared with the correlation values of that latent variable with other latent variables. The square root of AVE must be greater than the correlation values. This process is performed for all latent variables.

The results of the Fornell-Larcker criterion are presented in Table 3. One column in this table displays the square root of the average variance extracted (AVE). To confirm discriminant validity, the square root of AVE must be greater than the correlation coefficients of the variable with all other variables. For example, the square root of AVE for the causal conditions variable is 0.774, which is greater than its correlation with other variables. As shown in the table, the square root of AVE for all variables is higher than their correlations with other variables, confirming discriminant validity.

Table 3. Correlation Matrix and Square Root of AVE for the Main Model

Variable	Causal Factors	Contextual Factors	Intervening Factors	Strategies	Outcomes	Core Phenomenon
Causal Factors	0.774					
Contextual Factors	0.551	0.828				
Intervening Factors	0.478	0.598	0.806			
Strategies	0.418	0.474	0.523	0.823		
Outcomes	0.513	0.509	0.599	0.477	0.811	
Core Phenomenon	0.613	0.591	0.480	0.401	0.503	0.825

The Goodness-of-Fit (GOF) index evaluates the overall structural model fit in structural equation modeling (SEM). This index allows researchers to assess the overall fit of the measurement and structural model simultaneously. The GOF index was introduced by Tenenhaus et al. (2005), and Wetzels et al. (2009) suggested three threshold values: 0.01 (weak), 0.025 (moderate), and 0.36 (strong). The computed GOF value for this model is 0.478, indicating a strong fit, confirming the adequacy of the model.

The second part of the findings focuses on structural model testing and hypothesis validation. To test the research hypotheses, path coefficients and the coefficient of determination (R^2) were estimated using Partial Least

Squares (PLS) regression with Smart PLS software. The path coefficient indicates the contribution of each predictor variable to explaining the variance in the criterion variable.

To compute the t-statistics, the bootstrapping algorithm with 86 resampling subsamples was applied. Figure 1 presents the t-statistics for the path coefficients, while Figure 2 shows the final estimated structural model with standardized path coefficients.

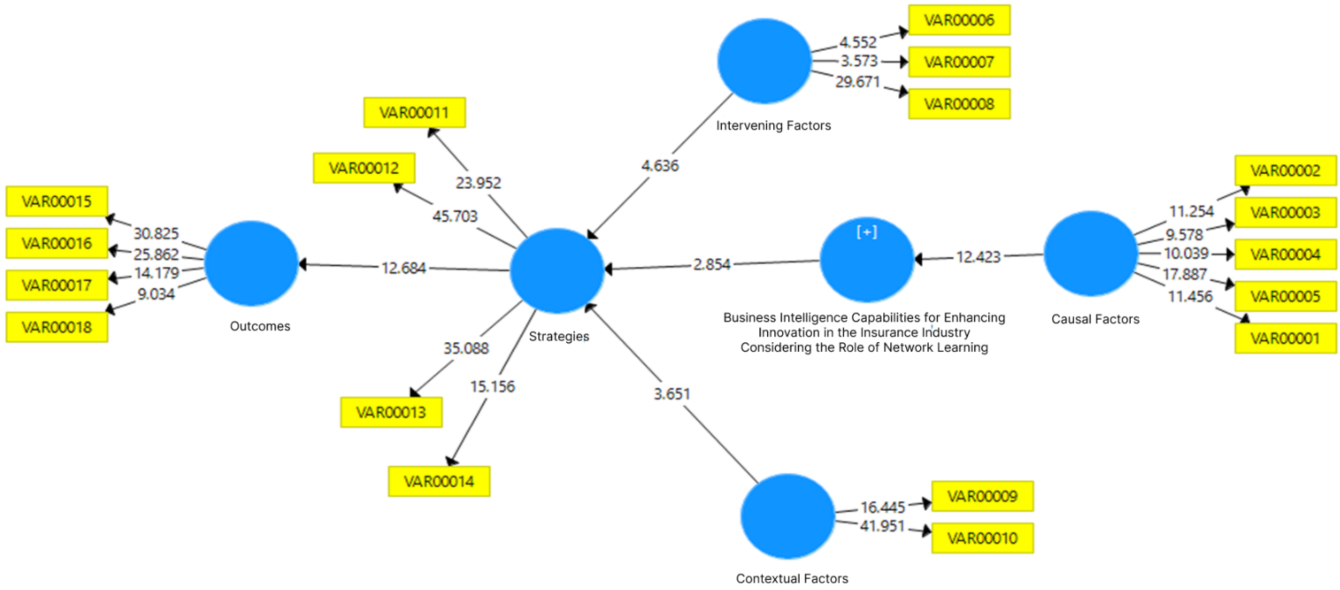

Figure 1. Structural Model in Significance Mode

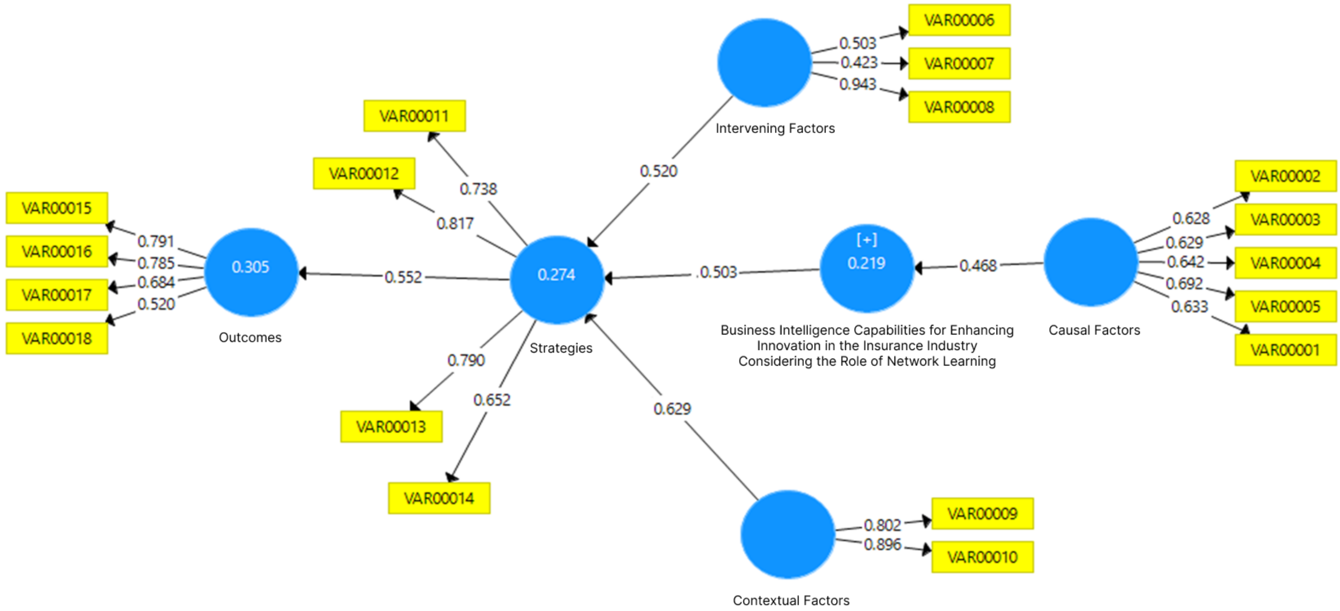

Figure 2. Structural Model in Standardized Mode

The overall research model depicted in the figures includes the measurement model (relationships between observed variables and latent variables) and the structural model (relationships among latent variables). Figure 1 presents the factor loadings of the research variables, derived from Smart PLS software. The model also provides standardized factor loadings summarizing the strength of relationships among research variables. To assess the significance of these relationships, t-statistics were calculated using bootstrapping, as shown in Figure 2. The results of hypothesis testing based on the relationships between variables are presented in the following section.

The hypotheses were tested based on the PLS regression analysis results, using factor loadings and bootstrapping techniques.

Table 4. Hypothesis Testing and Path Analysis Results

No.	Hypothesis	Path Coefficient	t-Statistic	Significance Level	Result
1	Causal conditions have a significant effect on the core phenomenon.	0.465	11.829	0.000	Confirmed
2	The core phenomenon has a significant effect on strategies.	0.503	7.727	0.000	Confirmed
3	Strategies have a significant effect on outcomes.	0.552	11.077	0.000	Confirmed
4	Intervening conditions have a significant effect on strategies.	0.520	2.756	0.000	Confirmed
5	Contextual conditions have a significant effect on strategies.	0.629	4.592	0.000	Confirmed

Based on the structural equation model results, all path coefficients in the hypotheses exceed 0.3, and all significance levels are below 0.05 ($p = 0.000$). With 95% confidence, it can be concluded that all hypotheses are confirmed.

4. Discussion and Conclusion

The findings of this study indicate that Business Intelligence (BI) capabilities have a significant impact on organizational innovation. Organizations that leverage BI systems can analyze big data, identify customer behavioral patterns, monitor market trends, and detect innovative opportunities. This enables them to make more precise and creative strategic decisions, which can contribute to an increased innovation rate in their products, services, and processes. Based on the findings, several recommendations can be proposed to enhance organizational innovation.

Organizations should invest more in advanced Business Intelligence systems to enhance their ability to analyze big data and extract valuable insights. The use of tools such as Power BI, Tableau, Google Analytics, and other advanced platforms can provide better decision-making insights. Developing a data-driven culture is essential, and managers should encourage data-based decision-making while promoting data utilization among employees. Conducting training programs on data analysis, machine learning, and artificial intelligence can enhance BI efficiency.

Strengthening network learning and inter-organizational collaborations can accelerate innovation and knowledge exchange. Establishing learning networks through partnerships with universities, research centers, and technology startups can provide organizations with access to emerging knowledge. Companies should also organize industry-specific events, conferences, and joint meetings to share experiences and expertise. Using BI to optimize innovation strategies can enable organizations to predict future needs and develop innovative products. Analyzing market trends and customer behavior through BI can help businesses anticipate shifts in demand and improve innovation processes. Organizations should leverage data from customer behavior, competitors, and global trends to create new products and optimize their innovation strategies.

Open innovation models should be adopted instead of relying solely on internal innovation. Organizations can utilize external knowledge sources for product development by participating in open collaboration platforms such as Innocentive, Kaggle, and GitHub to solve innovation challenges. Integrating BI systems with modern technologies, including artificial intelligence and machine learning, allows organizations to identify complex patterns in data and make more precise decisions. The adoption of predictive analytics models can help businesses identify growth opportunities and forecast market demand.

Continuous evaluation and monitoring of organizational performance are necessary to assess the impact of BI on innovation and business outcomes. Organizations should use key performance indicators (KPIs) such as return on investment (ROI), innovation rate, market share, and operational efficiency to analyze results. Analytical tools must be regularly updated to enhance accuracy and effectiveness.

This study has certain limitations that provide direction for future research. The study was conducted cross-sectionally, making causal inference challenging. The extensive number of questionnaire items prolonged the completion time, which may have affected the accuracy of participant responses. Since the research data were collected at a single point in time, future studies should extend the research period to obtain more reliable and accurate results.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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