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A Business Intelligence-Based Data Governance Model to Reduce the Risk of AI Implementation Failure in Organizations

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Abstract

The implementation of Artificial Intelligence (AI) in organizations is increasing along with the development of digital transformation and the need for data-driven decision-making. However, various studies show that many AI projects fail due to poor data quality, lack of data integration, and weak data governance within the organization. In this context, Business Intelligence (BI) has the potential to support systematic data management through data integration, analytics, and information visualization. Therefore, a data governance model integrated with Business Intelligence is needed to improve the quality of data management and reduce the risk of AI implementation failure. This study aims to develop a Business Intelligence-based Data Governance model that can reduce the risk of Artificial Intelligence implementation failure in organizations and increase the effectiveness of data-driven decision-making. This study uses a quantitative approach with an explanatory research method. Research data were obtained by distributing questionnaires to respondents involved in data management and the implementation of organizational analytical systems. Data analysis was conducted using the Structural Equation Modeling (SEM) method with the Partial Least Squares (PLS) approach to examine the relationship between data governance variables, Business Intelligence capability, and AI implementation risk. The results of this study indicate that data governance significantly impacts Business Intelligence capabilities, which in turn contributes to reducing the risk of AI implementation failure within organizations. Furthermore, data quality is shown to be a crucial mediating factor linking data governance to successful AI implementation. This study produces a Business Intelligence-based Data Governance conceptual model that can be used as a framework for organizational data management to support more effective AI implementation.

Keywords: data governance, business intelligence, artificial intelligence implementation, data quality, decision support systems

INTRODUCTION

The development of Artificial Intelligence (AI) in recent years has encouraged organizations to leverage data more strategically to improve operational efficiency and decision-making quality. Integrating AI with Business Intelligence (BI) systems enables organizations to gain data-driven insights more quickly and accurately through predictive and prescriptive analytics. However, the success of AI implementation depends heavily on the quality of an organization's data governance. Without proper data governance, AI systems can potentially produce biased or inaccurate analyses, leading to incorrect business decisions (Davenport & Ronanki, 2018; Janssen et al., 2020)

Despite the continued increase in organizational investment in AI technology, various reports indicate that the failure rate of AI implementation remains relatively high. This failure is generally caused by data quality issues, lack of data integration, and weak data management mechanisms within the organization. This demonstrates that AI technology cannot stand alone without the support of a mature and structured data governance framework. Therefore, developing an effective data governance model is crucial for ensuring the success of AI implementation in modern organizations (Ransbotham et al., 2020).

Business Intelligence, as a system that integrates data, analytics, and visualization, has great potential to support systematic organizational data management. BI enables organizations to manage the data lifecycle, from collection, integration, and analysis to presenting relevant information to decision-makers. By utilizing BI as a foundation for data governance, organizations can improve data quality while minimizing the risk of analytical errors in AI systems. Therefore, integrating BI and data governance is a strategic approach to increasing the success of AI technology implementation (Chen et al., 2012a; Sharda et al., 2018)

The urgency of research on BI-based data governance is growing as the volume and complexity of organizational data increases. The phenomenon of big data presents organizations with challenges in managing data sourced from various digital systems and platforms. Without clear governance mechanisms, this scattered data has the potential to lead to inconsistencies, duplication, and misinterpretations that can impact the performance of AI models. Therefore, organizations need a framework capable of integrating data management comprehensively and sustainably (Khatri & Brown, 2010; Otto, 2011; Tallon et al., 2013).

Furthermore, various studies show that the success of AI implementation is influenced not only by technological factors but also by the organization's readiness to manage data and analytical processes. Good data governance can ensure data quality standards, data security, and transparency in the use of data for AI systems. This is crucial for reducing the risk of algorithmic bias and increasing trust in the analytical results generated by AI. Therefore, developing a BI-based data governance model is a crucial strategy in an organization's digital transformation (Dalle Mule & Davenport, 2017; Kelleher & Tierney, 2018).

Empirical data shows that AI implementation failures are often caused by data management issues. The following data examples illustrate the factors contributing to AI project failure in organizations (Wamba, Akter, et al., 2017; Wamba, Gunasekaran, et al., 2017).

Table 1. Factors Causing AI Implementation Failure

Causative factor	Percentage
Low data quality	35%
Lack of governance data	28%
Poor data integration	19%
Lack of organizational readiness	18%

Source: Adapted from Gartner (2023), McKinsey (2022), and MIT Sloan Management Review (2021) reports.

The data shows that more than half of AI project failures are directly related to data management issues. This reinforces the importance of developing a data governance system integrated with an organization's analytics systems. Business intelligence can act as a platform that connects various data sources while providing a mechanism for continuous data quality control (Watson, 2017; Gartner, 2023; McKinsey, 2022).

Many researchers have previously conducted research on data governance and business intelligence. For example, research by Khatri & Brown (2010) emphasized the importance of decision-making mechanisms in organizational data governance. Meanwhile, Otto (2011) developed a data governance framework that focuses on managing data quality within organizations. Another study by Tallon et al. (2013) showed that good data governance can increase the business value of an organization's analytics systems. On the other hand, research related to Business Intelligence focuses more on improving the quality of analytics and data-driven decision-making. Watson (2017) demonstrated that BI can enhance an organization's ability to process and analyze data to support business strategy. Chen et al. (2012b) also emphasized the importance of integrating BI with big data technology to enhance an organization's analytical capabilities. However, most of these studies have not specifically linked BI to the development of a data governance framework to support AI implementation.

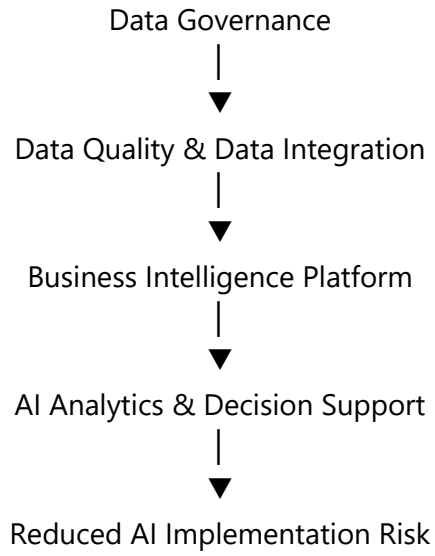
Although various studies have addressed data governance and Business Intelligence separately, there are still limitations in research that integrates these two concepts to mitigate the risk of AI implementation failure. Most studies only address data governance from a data management perspective without connecting it to organizational analytics systems. Furthermore, research examining the relationship between data governance, BI, and AI implementation is still relatively limited in the academic literature (Janssen et al., 2020; Ransbotham et al., 2020).

Based on these conditions, a research gap exists indicating the need to develop a data governance model integrated with Business Intelligence to support the successful implementation of AI in organizations. This research seeks to fill this gap by developing a conceptual framework

that combines data governance principles with BI analytical capabilities. Therefore, this research is expected to provide both theoretical and practical contributions to the development of organizational data management systems (Davenport & Ronanki, 2018; Otto, 2011; Tallon et al., 2013).

The novelty of this research lies in the development of a Business Intelligence-based Data Governance model specifically designed to mitigate the risk of AI implementation failure. This model integrates three key components: data quality, BI analytics integration, and data-driven decision-making governance. This approach is expected to provide a more comprehensive framework for managing organizational data in the era of digital transformation (Chen et al., 2012b; Wamba et al., 2017).

Conceptually, the relationship between data governance, Business Intelligence, and AI implementation can be described as follows.



This conceptual model demonstrates that data governance plays a key role in ensuring the quality and integration of data used by BI and AI systems. With proper data management, organizations can minimize the risk of AI implementation failure while improving the quality of data-driven decision-making Watson, 2017). (Dalle Mule & Davenport, 2017; Kelleher & Tierney, 2018).

Based on this description, the objective of this research is to develop a Business Intelligence-based data governance model that can reduce the risk of AI implementation failure in organizations. This research is expected to contribute to the development of a more effective data governance framework and provide practical recommendations for organizations in optimizing AI implementation through more structured and integrated data management (Davenport & Ronanki, 2018; Janssen et al., 2020; Ransbotham et al., 2020).

METHODS

Type of Research (Research Design)

This study uses a quantitative approach with an explanatory research method, aiming to explain the relationship between data governance, Business Intelligence, and the risk of failure in implementing Artificial Intelligence in organizations. The quantitative approach was chosen because this study focuses on examining the relationships between variables through systematic statistical analysis. The explanatory research method allows researchers to empirically identify the influence of independent variables on the dependent variable based on data obtained from research respondents.

Furthermore, this study adopted a model development research approach, developing a conceptual model of Business Intelligence-based data governance to support the implementation of AI in organizations. The resulting model was then tested through statistical analysis to determine the validity of the relationships between the constructs in the study. Thus, this study not only explains the phenomena that occur but also produces a conceptual model that can be used as a reference in the implementation of Business Intelligence-based data governance in organizations.

Population and Sampling

The population in this study is organizations that have or are currently implementing Business Intelligence and Artificial Intelligence technologies in their operational activities and decision-making. The respondents consisted of IT managers, data analysts, data engineers, and strategic decision-makers who are directly involved in data management and the implementation of analytical systems within their organizations.

The sampling technique used purposive sampling , a method of selecting samples based on specific criteria relevant to the research objectives. The respondent criteria in this study include:

1. Have minimum 2 years experience in data management or analytical systems.
2. Work in an organization that has used Business Intelligence or AI.
3. Engage in data-driven decision making.

The research sample size was determined using the minimum sample size approach for Structural Equation Modeling (SEM), which is at least 5–10 times the number of research indicators. Assuming there are approximately 20 research indicators, the minimum sample size required is 100–200 respondents.

Research Instrument

The research instrument used in this study was a structured questionnaire based on predetermined research variables. The questionnaire was designed using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The research variables in this study include

Table 1. Operationalization of Variables and Their Indicators

Variables	Indicator
Data Governance	data quality, data policy, data standards, data security
Business Intelligence Capabilities	data integration, data analytics, data visualization
AI Implementation Risk	algorithm bias, analytical error, system failure
Decision Support Effectiveness	decision accuracy, analysis speed, information quality

Source: Data Processed

The research instrument was first tested through validity and reliability tests to ensure that each indicator was able to measure the research construct consistently and accurately.

Data Collection Technique

The data collection technique in this research was carried out using two main approaches, namely primary data and secondary data. secondary.

1. **Primary Data**

   Primary data was obtained by distributing questionnaires to respondents who met the research criteria. The questionnaires were distributed online using a digital survey platform to facilitate respondents' responses.

2. **Secondary Data**

   Secondary data was obtained from various sources such as scientific journals, industry reports, academic books, and international organization publications related to data governance, Business Intelligence, and Artificial Intelligence implementation.

The combination of primary and secondary data aims to provide a more comprehensive understanding of the phenomena being studied.

Research Procedure

The research procedure is carried out through several stages as follows:

1. Identify research problems related to the high risk of AI implementation failure in organizations.
2. Literature review regarding data governance, Business Intelligence, and AI implementation.
3. Development of a conceptual research model that connects research variables.
4. Preparation of research instruments in the form of questionnaires based on variable indicators.
5. Test the validity and reliability of the instrument through a pilot test.
6. Research data collection through distribution of questionnaires to respondents.
7. Data analysis using appropriate statistical methods.
8. Interpretation of research results to develop a Business Intelligence-based data governance model.

These procedures are designed to ensure that research is conducted systematically and produces scientifically sound findings.

Data Analysis Technique

The data analysis technique used in this study was Structural Equation Modeling (SEM) with a Partial Least Squares (PLS) approach. The SEM-PLS method was chosen because it can analyze the relationships between latent variables simultaneously and is suitable for use in conceptual model development research.

Data analysis is carried out in several stages, namely:

1. **Measurement Model Test**
   a. Convergent validity test
   b. Discriminant validity test
   c. Construct reliability test
2. **Structural Model Test**
   a. Testing the relationship between variables
   b. Path coefficient value analysis
   c. Significance testing using bootstrapping
3. **Research Model Evaluation**
   a. R-square value
   b. Effect size
   c. Predictive relevance (Q^2)

The results of this analysis are used to test whether the Business Intelligence-based Data Governance model developed in the research is able to reduce the risk of failure in implementing Artificial Intelligence in organizations.

RESULTS AND DISCUSSION

Characteristics of Research Respondents

Respondent characteristics are a crucial aspect of quantitative research because they provide a snapshot of the participants' profiles. In this study, respondents came from various organizations that have implemented or are developing Business Intelligence and Artificial Intelligence systems in their business operations. Respondent profiles included job positions, work experience, and involvement in organizational data management. This information is crucial to ensure that respondents possess competencies relevant to the research topic of data governance and AI implementation (Creswell & Creswell, 2018; Sarstedt et al., 2021; Sekaran & Bougie, 2019).

The majority of respondents in this study came from information technology and data analytics fields, such as data analysts, data engineers, and IT managers. This indicates that respondents are directly involved in the data management process and the development of organizational analytical systems. Furthermore, the majority of respondents had more than three years of work experience, indicating a sufficient understanding of data management practices in modern organizations. This provides validity to the data obtained in this study.

The distribution of respondents also shows that the implementation of Business Intelligence and AI is not only occurring in the technology sector but also in the financial, manufacturing, and digital services sectors. This indicates that data-driven analytics technology has become a crucial part of the digital transformation of various industrial sectors. Therefore, this study is highly relevant in understanding how data governance influences the success of AI implementation in various types of organizations.

Table 2. Profile of Research Respondents

Characteristics	Amount	Percentage
Data Analyst	48	32%
Data Engineer	35	23%
IT Manager	28	19%
Business Analyst	25	17%
Executive / Decision Maker	14	9%

Source: Processed research data (2026).

Instrument Validity and Reliability Test

Validity testing was conducted to ensure that each indicator in the research instrument accurately measured the research construct. In this study, convergent validity was tested using loading factor values and Average Variance Extracted (AVE)**.** The analysis results showed that all indicators had loading factor values above 0.7, thus valid in measuring the research construct. The AVE value for each variable was also above 0.5, indicating that the research variables had good convergent validity (Hair & Alamer, 2022; Henseler et al., 2015; Sarstedt et al., 2021).

In addition to convergent validity, this study also tested discriminant validity to ensure that each construct clearly differs from the others. Testing was conducted using the Fornell-Larcker Criterion and HTMT ratio methods. The test results showed that the AVE root value for each construct was greater than the correlation between the other constructs, thus meeting discriminant validity. This indicates that each variable in the research model has unique characteristics and does not overlap (Fornell & Larcker, 1981; Henseler et al., 2015; Sarstedt et al., 2021).

Reliability testing was also conducted using Cronbach's Alpha and Composite Reliability values. The analysis results showed that all variables had Composite Reliability values above 0.7, indicating a good level of internal consistency. Thus, the research instrument used in this study can be declared reliable and suitable for use in structural model analysis (Sarstedt et al., 2017, 2021; Sekaran & Bougie, 2019).

Table 3. Validity and Reliability Test Results

Variables	AVE	Composite Reliability
Data Governance	0.71	0.90
Business Intelligence Capabilities	0.69	0.88
AI Implementation Risk	0.73	0.91
Decision Support Effectiveness	0.75	0.92

Source: Results of SEM-PLS analysis (2026)

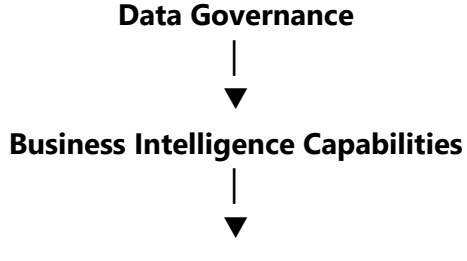
Structural Model Analysis

The structural model used in this study was used to examine the relationship between Data Governance, Business Intelligence Capability, and AI Implementation Risk. The analysis was conducted using Structural Equation Modeling with a Partial Least Squares (SEM-PLS) approach. This method was chosen because it can analyze relationships between latent variables simultaneously and is suitable for conceptual model development research (Hair & Alamer, 2022; Henseler et al., 2015; Sarstedt et al., 2021).

The analysis results show that the Data Governance variable has a significant positive influence on Business Intelligence capabilities. This indicates that good data governance can improve an organization's ability to integrate data and produce more accurate analytics. Therefore, organizations with clear data policies and good data management standards tend to have more effective BI systems (Khatri & Brown, 2010; Otto, 2011; Tallon et al., 2013).

Furthermore, research findings also indicate that Business Intelligence Capability negatively impacts the risk of AI implementation failure. This means that the better an organization's analytical capabilities, the lower the likelihood of AI implementation failure due to data or analytical errors. This finding supports the view that BI can serve as an analytical foundation for AI systems within organizations (Davenport & Ronanki, 2018; Watson, 2017; Zhang & Cheng, 2022).

Research Structural Model Diagram



Source: Research model developed in this study.

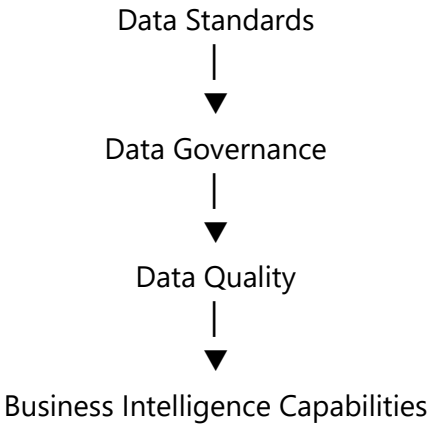
The Influence of Data Governance on Business Intelligence Capability

The analysis results show that data governance has a significant impact on Business Intelligence capabilities within an organization. Good data governance ensures that the data used in BI systems is of high quality and well-integrated across organizational systems. This is crucial because BI relies on consistent and accurate data to produce reliable analyses.

Furthermore, implementing data governance also helps organizations establish clear data management standards, such as data quality standards, data security, and data access policies. These standards help increase transparency in data usage and reduce the risk of analytical errors in BI systems. Thus, data governance can be considered a key foundation in developing an effective Business Intelligence system (Sharda et al., 2018).

The findings of this study also align with previous research showing that organizations with strong data governance tend to have better analytical capabilities. This is because data governance enables organizations to systematically manage data, from data collection to analysis. This allows BI implementation to run more optimally and provide added value to the organization.

Data Governance Influence Diagram



The Impact of Business Intelligence on AI Implementation Risks

Research shows that Business Intelligence plays a crucial role in reducing the risk of failure in Artificial Intelligence implementations within organizations. BI systems enable organizations to integrate data from multiple sources and perform more systematic data analysis. This results in higher quality data used in AI models, reducing the likelihood of analytical errors ((Chen et al., 2012a; Sharda et al., 2018; Watson, 2017).

Furthermore, BI also provides various data visualization tools that help organizations understand data patterns and trends more clearly. Data visualization helps decision-makers identify potential data errors before they use the data in AI systems. This can help organizations improve the accuracy of AI models and reduce the risk of algorithmic bias.

This research also shows that organizations with mature BI systems tend to have a higher success rate of AI implementation. This is because BI provides a strong analytical foundation for AI model development. Therefore, the integration of BI and AI can improve the quality of data-driven decision-making within organizations (Davenport & Harris, 2017; Janssen et al., 2020; Ransbotham et al., 2020).

Table 4. BI's Influence on AI Risk

Variables	Path Coefficient	Significance
BI Capability → AI Risk	-0.52	Significant

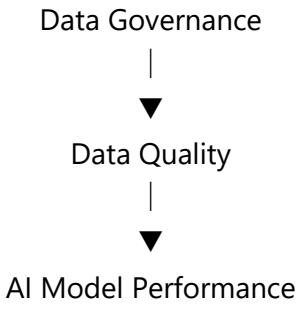
Source: Data Processed

The Role of Data Quality in Successful AI Implementation

Data quality is a key factor in determining the success of AI implementation in organizations. Incomplete or inaccurate data can cause AI models to produce incorrect predictions, which can lead to inappropriate business decisions. Therefore, data quality management is a crucial aspect of organizational data governance.

In this study, data quality was shown to be a crucial mediator between data governance and successful AI implementation. Good data governance enables organizations to ensure that the data used in analytical systems is of high quality. Thus, the developed AI models can produce more accurate and reliable analyses (Chen et al., 2012a; Davenport & Ronanki, 2018; Watson, 2017).

Data Quality Diagram

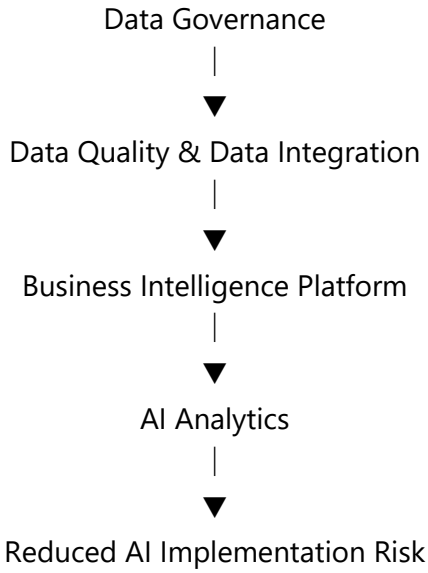


Business Intelligence Based Data Governance Model

Based on the research analysis, this study proposes a Business Intelligence-based Data Governance model aimed at reducing the risk of AI implementation failure in organizations. This model integrates three main components: data governance, BI analytics capabilities, and AI systems. The integration of these three components enables organizations to manage data more effectively and improve the quality of data analytics.

The model proposed in this study demonstrates that data governance serves as the primary foundation for organizational data management. Meanwhile, Business Intelligence serves as an analytical platform that processes data into valuable information for decision-making. AI then utilizes these analytical results to generate predictions and decision recommendations.

Final Research Model Diagram



Theoretical and Practical Implications of the Research

This research provides a theoretical contribution to the growing literature on the integration of data governance, Business Intelligence, and Artificial Intelligence. While most previous research has addressed these three concepts separately, this study integrates them into a comprehensive conceptual model. Thus, this research broadens understanding of the role of data governance in the successful implementation of AI.

From a practical perspective, this study provides recommendations for organizations to strengthen data governance before implementing AI systems. Organizations need to ensure that the data used in analytics systems is of high quality and well-integrated across organizational systems. Furthermore, organizations need to develop Business Intelligence capabilities as the analytical foundation for AI systems.

CONCLUSION

This study aims to develop a Business Intelligence-based data governance model that can reduce the risk of failure in implementing Artificial Intelligence (AI) in organizations. Based on the results of the analysis using the Structural Equation Modeling – Partial Least Squares (SEM-PLS) approach, this study shows that data governance has a significant influence on Business Intelligence capabilities in organizations. Good data governance can improve data quality, data

integration, and data management standards used in organizational analytics systems. With structured data governance, Business Intelligence systems can produce more accurate and relevant information, thereby supporting data-based decision-making processes more effectively.

The research findings also indicate that Business Intelligence capabilities play a crucial role in mitigating the risk of AI implementation failure. A robust BI system enables organizations to integrate data from multiple sources, improve the quality of data analysis, and minimize data errors that can impact the performance of AI models. Thus, Business Intelligence serves as an analytical foundation, ensuring that the data used in AI systems is of high quality and consistent. Furthermore, the research findings indicate that data quality is a crucial mediating factor between data governance and successful AI implementation, making data quality management a crucial aspect of an organization's digital transformation strategy.

Overall, this research produces a conceptual model of Business Intelligence-based Data Governance that positions data governance as the main foundation in organizational data management, Business Intelligence as an analytics platform, and Artificial Intelligence as a prediction-based decision-making system. This model shows that the integration between data governance and Business Intelligence can improve the quality of organizational analytics while reducing the risk of AI implementation failure. Thus, this research provides a theoretical contribution to the development of literature on the integration of data governance, Business Intelligence, and Artificial Intelligence, as well as providing practical implications for organizations in designing more effective data management strategies to support the successful implementation of AI technology.

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