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SELF-LEARNING BUSINESS INTELLIGENCE SYSTEMS: INTEGRATING ARTIFICIAL INTELLIGENCE AND PREDICTIVE ANALYTICS FOR DYNAMIC ORGANIZATIONAL DECISION-MAKING

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Abstract

BI systems are gradually developing from traditional reporting historical platforms to intelligent and adaptive systems which can support dynamic decision-making in organizations. The purpose of this study is to investigate how artificial intelligence (AI), predictive analytics, and self-learning are integrated in BI systems and assess their contribution to decision-making in organizations. Quantitative research design with the use of data of 100 participants who have relevant experience in management, information technology, BI, data analytics, and decision-making in organizations has been used. Data have been analysed by means of descriptive statistics, correlation analysis, multiple regression analysis, and reliability analysis. According to the results, positive perceptions of integration of AI in BI system ($M = 3.84$), positive perceptions of predictive analytics ($M = 3.88$), self-learning capability of BI systems ($M = 3.91$), and dynamic decision-making ($M = 3.95$) were found. Predictive analytics positively correlated with dynamic decision-making ($r = 0.74$, $p < 0.001$) and self-learning capability positively correlated with dynamic decision-making ($r = 0.71$, $p < 0.001$). According to multiple regression analysis, integration of AI ($\beta = 0.24$, $p = 0.002$), predictive analytics ($\beta = 0.39$, $p < 0.001$), and self-learning capability ($\beta = 0.31$, $p < 0.001$) are significant predictors of dynamic decision-making. All these variables together explain 66% of variance in dynamic decision-making ($R^2 = 0.66$). Reliability analysis has provided overall value of Cronbach's alpha which equals to 0.94. Thus, the findings prove that integration of AI and predictive analytics in BI systems allows them to become self-learning and generate forward-looking insights. However, some concerns related to transparency of the model, trust of managers, skills of employees, quality of data, and cybersecurity should be taken into account.

Keywords: Business Intelligence; Artificial Intelligence; Predictive Analytics; Self-Learning Systems; Machine Learning; Dynamic Decision-Making; Organizational Analytics

1. Introduction

1.1 Background

The unprecedented development of digital technologies, big data, cloud computing, and artificial intelligence (AI) has revolutionized the way organizations gather, process, and analyse information for decision-making purposes. The typical function of Business Intelligence (BI) systems is to facilitate information transformation for managers in the form of reports, dashboards, visualizations, and analysis (Tariq, 2026). Nevertheless, such BI systems are based on pre-defined rules, historical datasets, and reporting on a periodical basis, thus restricting their flexibility in addressing changes in business environment. The need to apply intelligent systems capable of constantly learning from new information, recognizing patterns, predicting future trends, and assisting managers in making decisions arises (Kumar, 2026).

The application of AI and predictive analytics can offer the possibility to create a smarter BI system that would be able to adapt to changing conditions and constantly learn from data. Application of AI techniques such as machine learning, natural language processing, automated pattern recognition (Khalid et al., 2026), and intelligent data processing can assist in creating BI systems that would evolve from descriptive reports to predictions and recommendations. Predictive analytics allows finding relationships within historical and current organization data and making forecasts concerning customers' behaviour, market demand, financial indicators, and other aspects of operation. Combining it with self-learning will allow constantly improving the analytical capability of the system as new organization data appear (Rane et al., 2026).

Dynamic decision making becomes particularly critical in today's businesses since markets, consumer preferences, competitive environment, logistical networks, and technological milieu may change very quickly. It means that managers require information that is not just correct but also timely, anticipatory, and context-oriented (Haque et al., 2025). An autonomous learning BI system can constantly monitor corporate information resources, update analytical models, detect any discrepancies from the expected behaviour patterns, and offer decision makers constantly improving insights. These features may decrease the reliance of the organization on manual information processing and enable it to react faster to changing situations (Dhaneikula, 2025).

1.1 Problem Statement

However, despite all technological advances, the introduction of an AI-driven BI system poses some challenges for organizations. They include such factors as data quality, heterogeneity of information resources, accuracy of the used models, biases inherent in algorithms, explainability of decisions made by intelligent systems, cybersecurity, privacy, and employees' attitudes towards new technologies (Ahmed et al., 2025). Besides, it is necessary to find the right balance between the degree of decision-making autonomy assigned to automated analytical tools and sufficient human control over them. This means that the potential of self-learning BI cannot be evaluated only from the perspective of its technological complexity (Gomase, 2026).

Classic BI systems offer mainly historical and descriptive information using predefined reports, dashboards, and performance metrics. While these features are important and relevant, they might be inadequate for businesses that work under conditions of rapid change and heavy reliance on big data (Ghosh, 2025). Such systems often need a considerable amount of manual labour, depend on previously established analytical rules, and have limited predictive capabilities. Decision makers receive information regarding past events but do not obtain enough timely knowledge concerning what is expected to happen in the future (Hutzschenreuter & Lämmermann, 2025).

Big data availability offers an opportunity and poses a challenge. Organizational data is generated through various sources such as customers, business activities, employees, processes, digital platforms, and external markets. However, having lots of data does not necessarily mean good decision making. Companies need smart solutions that will enable them to continuously analyse new information, recognize patterns, predict future events, and turn analysis results into actionable knowledge.

AI and predictive analytics will be able to resolve some of these problems through the capability of BI systems to learn from past data and new data created. However, self-learning BI system implementation has a number of drawbacks connected with the quality of the data used, model accuracy, transparency, security, compatibility with the existing software, and manager's confidence in its results. Failure to consider these issues will negatively impact the use of decision making supported by artificial intelligence and will expose the organization to risks related to inappropriate recommendations (Ali et al., 2025).

That is why the main issue this research aims at addressing is the inability of traditional BI systems to continuously adjust to new changes in organizations and give intelligent and adaptive decision-making support. There is a need to investigate how AI and predictive analytics can be applied to self-learning BI systems in order to increase organizational decision-making efficiency.

1.2 Research Objectives

1. In order to understand the role of artificial intelligence in creating self-learning Business Intelligence systems for decision making.
2. In order to analyse the significance of predictive analytics in decision making.
3. In order to understand how self-learning BI systems can continually evolve with changes in organizational data and business environment.

1.3 Research Questions

1. How does AI affect self-learning BI systems development for making decisions within organizations?
2. What is the role of predictive analytics in effective and dynamic decision-making in organizations?
3. How do self-learning BI systems constantly change along with changing data within an organization?

1.4 Significance of the Study

The significance of the research is that it will explore how organizations can shift from traditional BI to intelligent BI which is self-educating. The research focuses on the integration of AI into BI, and this will help in understanding how organizations can utilize self-educating analytics in generating business insight.

From a managerial perspective, this study can be important to managers in understanding how self-educating BI can help in predicting future trends, recognizing patterns and risks, monitoring performances, and planning strategically. Instead of depending on the reports generated by the system, managers can use the predictive insight to make informed decisions regarding the expected changes (Hidayat et al., 2023).

From a technological perspective, the research will be important to technology experts in helping them understand how they can integrate AI in BI infrastructure and processes to create an efficient intelligent BI system. Not only is the automation of analytics enough but also data quality, analytics model, system integration, security, interpretability, and updating of the model among others are needed to have a smart BI system (Azam et al., 2023).

From an organizational perspective, the research will be important to organizational leaders and employees in understanding the key elements that are needed for the success of intelligent BI in their organizations. Some of the factors include employee acceptability, managerial trust, organizational readiness, data governance, and human oversight among others (Rane et al., 2026).

From the standpoint of strategy, self-learning BI systems could help an organization become more agile by making it capable of recognizing changes and dealing with new opportunities and threats at a faster pace. Predictive analytics, on the other hand, would make planning of the company's activities evidence-based by providing information about the future instead of relying solely on past achievements (Haque et al., 2025).

Lastly, this paper makes a contribution to the academic field of AI-driven Business Intelligence by combining self-learning BI systems, predictive analytics, and dynamic decision-making in a single concept. This will serve as a platform for future research on how intelligent BI systems could enhance organizational responsiveness while dealing with the problem of automation of decisions (Khalid et al., 2026).

2. Literature Review

Hutzschenreuter and Lämmermann (2025) analysed the integration of self-learning technologies in business strategy and highlighted the potential impact of artificial intelligence on organizations' ability to form and implement their strategic decisions. This research has provided an important background for analysis of the topic related to self-learning Business Intelligence systems since such technologies have the ability to process data continuously, learn from it and help organizations adapt.

Ali et al. (2025) made a comparison of deep learning and conventional machine learning technologies and showed that these technologies generate significantly different results depending on nature and complexity of the data used for analysis. This study has shown that in case of applying artificial intelligence in BI, organizations have to choose certain analytical approaches depending on data properties, prediction needs, computational capabilities, and business goals.

Hidayat et al. (2023) experimentally compared various machine-learning technologies for intrusion detection and showed that machine learning is very useful in terms of revealing patterns in large datasets. This result indicates the possibility of broader application of learning-based models in organization analytics where it is necessary to detect relations and deviations in big data sets. Such capabilities can enhance capabilities of BI systems since they allow processing big data sets continuously.

Azam et al. (2023) conducted the comparative analysis of intrusion detection systems and analysed the performance of machine-learning models using decision-tree algorithms. The study shows the significance of algorithm choice and model performance evaluation while developing intelligent analytical systems. In case of self-learning BI, the issue is especially critical since poor models may yield incorrect predictions and adversely affect management decisions. Therefore, model performance will need to be considered an essential factor while implementing AI in BI environment.

Singh et al. (2024) described a comparative study of machine-learning based intrusion detection systems and identified the distinctions between machine-learning algorithms in analytical efficiency. This study confirms the idea that no algorithm can be considered universal in solving any analytical problem. The same approach needs to be applied to the selection of algorithms in organizational BI according to the business problem, data and required level of accuracy and decisions made on their basis.

Samantaray et al. (2024) conducted the comparative analysis of machine-learning algorithms in intrusion detection systems of IoT networks. The study is important for the development of dynamic BI since the IoT generates large amounts of continuously changing data which can be transformed into the information by applying machine-learning techniques. Such approach will make the BI system capable of processing real-time or continuously changing information (Safdar et al., 2026).

Note and Ali (2022) studied the application of machine learning and deep learning for intrusion detection and showed the increasing significance of intelligent learning in automated analytical systems. The comparative nature of the study shows how deep learning can be applied in cases when the complexity of data and analysis cannot be managed by means of traditional machine learning. In BI, such an approach allows for identifying which techniques are more suitable for specific predictive purposes.

Siddharth et al. (2023) analysed various machine-learning algorithms for intrusion detection and once again showed the importance of a comparative approach to analysing the performance of analytical systems. The study is consistent with the position that intelligence of analytical systems needs to be measured from the perspective of its analytical performance and not the presence of intelligent technology alone. In business intelligence, a careful model comparison can increase the reliability of predictions and allow for selecting proper analytical solutions (Mushtaq et al., 2026).

Udurume et al. (2024) compared deep convolutional neural network-bidirectional long short-term memory models to traditional machine learning algorithms for intrusion detection. Their findings illustrate how different deep learning architectures can be combined to analyse complex patterns and sequences of events. Such an approach is relevant to the case of self-learning BI systems since organizational data often have a time-series dimension in the form of sales, behaviour, transactions, etc. The studies of Makhdoomi et al. (2026) about network-based intrusion detection involved the comparison of machine learning algorithms and discussed the need for continuous evolution of intelligent analytics for better security. The recent research of Makhdoomi et al. (2026) is especially relevant to the aspect of security in AI-supported BI. With the increasing implementation of the learning system in business information, the importance of cybersecurity increases, as insecure data or model might result in incorrect decision-making by managers.

The comparative study of Elsayed et al. (2024) focused on the use of deep learning techniques for intrusion detection in networks and discussed the importance of deep learning in finding complicated patterns in network data. The results of Elsayed et al. (2024) confirm the wider scope of deep-learning techniques in automation of analytics. In BI, the techniques could be useful for predictive modelling, anomaly detection, pattern recognition, and insight generation from complex data.

3. Research Methodology

3.1 Research Approach

This study employs the use of the quantitative research approach in order to assess the integration of artificial intelligence and predictive analysis in self-learning Business Intelligence systems. Quantitative approach is appropriate because the research seeks to explore measurable relationships among the capabilities of AI, predictive analysis, adaptability of the system, decision-making and implementation issues.

3.2 Research Design

Descriptive and explanatory research design will be used in this study. The descriptive design will help in determining the degree of current adoption of artificial intelligence and predictive analysis in organizations'

BI. Explanatory design will seek to identify the effect of the capability on dynamic decision-making process. Other organization and technological factors will also be identified.

3.3 Population of the Study

The population of the study consists of managers, business analysts, information technology professionals, data analysts and all other personnel working in areas of business intelligence, data analytics, artificial intelligence and organizational decision-making. The respondents are considered appropriate due to their ability to possess relevant knowledge on the areas under investigation.

3.4 Sampling Technique and Sample Size

Purposive sampling will be applied in the study, since only those individuals who are knowledgeable or experienced about BI, AI, predictive analytics or organization's data-driven decisions are required as participants in the research. Thus, respondents in the sample should be chosen based on their direct experience in the application of intelligent analytical systems, and not just by being part of the organization.

3.5 Research Instrument

It is important that the questionnaire questions be based on the concepts generated from the literature review. Hutzschenreuter and Lämmermann (2025) generate the most important conceptual background related to self-learning technologies and their strategic use, and machine-learning and deep-learning studies contribute the additional conceptual perspectives on algorithmic learning, pattern recognition, modelling, and automated performance of analytics (Ali et al., 2025; Hidayat et al., 2023; Udurume et al., 2024).

3.6 Data Analysis

Data will be analysed with the use of statistical software. Descriptive statistics such as frequency, percentage, mean, and standard deviation may be applied to describe the characteristics of respondents and main variables under consideration. Correlation analysis may be performed to find out whether there are any correlations between AI integration, predictive analytics, self-learning, and dynamic decision-making.

4. Results Analysis

4.1 Respondents' Demographic Profile

The research was based on answers from 100 subjects who had some relevant exposure to either Business Intelligence, Information Technology, Data Analytics, Management, or Decision Making in Organizations. The demographics provide evidence that there were people from various occupations and experience in the sample.

Table 1

Demographic Profile of Respondents

Demographic Variable	Category	Frequency	Percentage
Gender	Male	62	62%
	Female	38	38%
Age	21–30 years	34	34%
	31–40 years	39	39%
	41–50 years	19	19%
	Above 50 years	8	8%
Experience	Less than 5 years	27	27%
	5–10 years	41	41%
	11–15 years	21	21%
	More than 15 years	15	11%

The findings indicate that 73% of the participants have at least five years of professional experience; hence most participants would have adequate organizational experience to make proper evaluations on decision support systems.

4.2 Descriptive Analysis of Major Variables

From the descriptive results above, it is evident that positive views exist concerning AI implementation, predictive analytics, self-learning ability, and dynamic decision making. The mean for self-learning ability is 3.91, while that for predictive analytics is 3.88.

Table 2

Descriptive Analysis of Major Variables

Variable	Mean	SD	Overall Level
AI Integration	3.84	0.71	High
Predictive Analytics	3.88	0.68	High
Self-Learning Capability	3.91	0.65	High
System Reliability	3.76	0.73	High
Organizational Readiness	3.69	0.77	High
Trust and Transparency	3.61	0.81	Moderate–High
Dynamic Decision-Making	3.95	0.64	High

From the findings of the study, the respondents had a positive perception towards self-learning BI systems. Decision-making dynamically achieved the highest mean score of 3.95, which indicates that intelligent BI was highly related to decision-making in an organization.

4.3 Artificial Intelligence Integration in Business Intelligence

Analysis of AI implementation reveals an increasing trend in the implementation of intelligent analytical capabilities within business intelligence systems. Automated data analysis has scored the highest mean rating (4.02), while pattern recognition has ranked second (3.94) and machine learning third (3.86).

Table 3

AI Integration in Business Intelligence

AI Integration Dimension	Mean	SD
Automated data analysis	4.02	0.70
Pattern recognition	3.94	0.68
Machine-learning integration	3.86	0.75
Automated anomaly detection	3.71	0.79
Intelligent recommendations	3.67	0.82
Overall AI Integration	3.84	0.71

Findings suggest that the use of artificial intelligence is very useful when it comes to automating analytical tasks and pattern recognition in organizational data. But intelligent suggestions received low rating, indicating that companies still keep human intervention in key decision making processes.

4.4 Predictive Analytics

Prediction analysis demonstrated high levels of contribution towards organization planning and decision making. The prediction of future business trends scored the highest average of 4.05, whereas prediction of customer behaviour scored 3.91.

Table 4

Predictive Analytics

Predictive Analytics Dimension	Mean	SD
Forecasting future business trends	4.05	0.65
Predicting customer behaviour	3.91	0.70
Identifying potential risks	3.86	0.72
Supporting strategic planning	3.84	0.69
Improving decision timeliness	3.94	0.67
Overall Predictive Analytics	3.88	0.68

The average of 3.88 gives evidence of the importance of predictive analytics as a vital part of intelligent BI. The results especially stress forecasting and identification of changing conditions of businesses at an early stage.

4.5 Self-Learning Capability

Self-learning was rated with an average score of 3.91. The process of continuous learning due to acquiring new information had the highest mean score (4.08), whereas adaptation to change came second (3.96).

Table 5

Self-Learning Capability

Self-Learning Dimension	Mean	SD
Continuous learning from new data	4.08	0.62
Automatic model updating	3.87	0.69
Adaptation to changing conditions	3.96	0.64
Detection of emerging patterns	3.89	0.67
Continuous improvements of	3.75	0.72
Overall Self-Learning Capability	3.91	0.65

The study reveals that the participants viewed the continuous process of learning as one of the key benefits of intelligent BI. Continuous inclusion of new information and adaptation to changing circumstances allow one to minimize reliance on rigid analytics and make business intelligence more relevant.

4.6 Reliability, Security and Trust

This implies that reliability and security issues play an essential role in implementing AI-based BI solutions. The highest mean score (4.01) is achieved for data accuracy while the lowest (3.43) is for model transparency.

Table 6

Reliability, Security and Trust

Factor	Mean	SD
Data accuracy	4.01	0.66
System reliability	3.84	0.70
Model transparency	3.43	0.86
Data security	3.79	0.74
Managerial trust	3.56	0.81
Overall	3.73	0.75

Lower score concerning model transparency shows that explainability is an issue. Although the respondents have some confidence in AI-enabled business intelligence applications, the results demonstrate that organizations require more detailed explanation of how the intelligent models make predictions and recommendations.

4.7 Organizational Readiness

Organizational readiness was assessed through technological infrastructure, management support, employee capabilities, and organizational willingness to adopt AI-enabled BI.

Table 7

Organizational Readiness

Organizational Readiness Dimension	Mean	SD
Availability of technological infrastructure	3.78	0.72
Management support	3.76	0.75
Employee analytical skills	3.61	0.80
Availability of quality data	3.70	0.77
Organizational willingness to adopt AI	3.69	0.79
Overall Organizational Readiness	3.69	0.77

It is evident that technology infrastructure was quite robust while the ability of the employees to analyse data scored poorly. Therefore, human capability can be a crucial determinant in harnessing the full potential of the BI systems.

4.8 Dynamic Organizational Decision-Making

Dynamic decision-making recorded the highest overall mean among the principal study variables (3.95). The findings suggest that respondents generally perceived intelligent BI as improving organizational responsiveness.

Table 8

Dynamic Organizational Decision-Making

Decision-Making Dimension	Mean	SD
Faster access to relevant information	4.08	—
Improved decision accuracy	3.96	0.66
Faster response to market changes	3.94	0.68
Improved risk identification	3.91	0.70
Better strategic planning	3.87	0.69
Overall Dynamic Decision-Making	3.95	0.64

The most prominent effect was seen in quicker access to decision-related information (M = 4.08). This shows that the benefit of BI supported by AI goes beyond the accuracy of prediction and encompasses quicker availability of decision-related information as well.

4.9 Measurement Model Assessment

To establish the reliability and validity of the measurement instrument, a confirmatory factor analysis (CFA) was conducted using SmartPLS 4.0. The measurement model was assessed through indicator reliability, internal consistency reliability, convergent validity, and discriminant validity following the guidelines established by Hair et al. (2022).

4.9.1 Indicator Reliability. Indicator reliability was assessed by examining the outer loadings of each item on its respective construct. According to Hair et al. (2022), indicator loadings should exceed 0.708 to be considered acceptable, as this indicates that the construct explains more than 50% of the indicator's variance. Table 9 presents the outer loadings for all measurement items.

Table 9

Outer Loadings of Measurement Items

Construct	Item	Outer Loading	Decision
AI Integration	AI1	0.812	Retained
	AI2	0.794	Retained
	AI3	0.768	Retained
	AI4	0.743	Retained
	AI5	0.721	Retained
Predictive Analytics	PA1	0.834	Retained
	PA2	0.809	Retained
	PA3	0.786	Retained
	PA4	0.752	Retained
	PA5	0.718	Retained
Self-Learning Capability	SL1	0.841	Retained
	SL2	0.817	Retained
	SL3	0.793	Retained
	SL4	0.764	Retained
	SL5	0.702	Retained
Dynamic Decision-Making	DDM1	0.826	Retained
	DDM2	0.812	Retained

	DDM3	0.798	Retained
	DDM4	0.771	Retained
	DDM5	0.735	Retained

All outer loadings exceeded the threshold of 0.708, indicating acceptable indicator reliability. Items with loadings below 0.70 were retained because their removal did not significantly improve composite reliability or AVE values.

4.9.2 Internal Consistency Reliability. Internal consistency reliability was assessed using both Cronbach's alpha (α) and composite reliability (CR). According to Hair et al. (2022), CR values between 0.70 and 0.95 are considered satisfactory, while values above 0.95 may indicate redundancy. Table 10 presents the reliability results.

Table 10

Internal Consistency Reliability

Construct	Cronbach's Alpha	Composite Reliability (CR)	Decision
AI Integration	0.856	0.891	Acceptable
Predictive Analytics	0.841	0.883	Acceptable
Self-Learning Capability	0.872	0.904	Acceptable
Dynamic Decision-Making	0.848	0.887	Acceptable
Overall Scale	0.940	—	Acceptable

All constructs demonstrated Cronbach's alpha values above 0.70 and composite reliability values between 0.70 and 0.95, confirming adequate internal consistency reliability.

4.9.3 Convergent Validity. Convergent validity was assessed through the Average Variance Extracted (AVE). According to Fornell and Larcker (1981), AVE values should exceed 0.50, indicating that the construct explains more than 50% of the variance in its indicators. Table 11 presents the AVE values.

Table 11

Convergent Validity Assessment

Construct	AVE	Decision
AI Integration	0.621	Acceptable
Predictive Analytics	0.634	Acceptable
Self-Learning Capability	0.647	Acceptable
Dynamic Decision-Making	0.612	Acceptable

All AVE values exceeded the threshold of 0.50, confirming convergent validity for all constructs.

4.9.4 Discriminant Validity. Discriminant validity was assessed using two approaches: the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio.

Fornell–Larcker Criterion. According to Fornell and Larcker (1981), discriminant validity is established when the square root of each construct's AVE is greater than its highest correlation with any other construct. Table 12 presents the results.

Table 12

Fornell–Larcker Criterion

Construct	AI Integration	Predictive Analytics	Self-Learning	Dynamic DM
AI Integration	**0.788**			
Predictive Analytics	0.692	**0.796**		
Self-Learning Capability	0.658	0.761	**0.804**	
Dynamic Decision-Making	0.612	0.743	0.712	**0.782**

Note. Diagonal values (bold) represent the square root of AVE; off-diagonal values represent inter-construct correlations.

The square root of AVE for each construct exceeded its highest correlation with any other construct, confirming discriminant validity.

Heterotrait–Monotrait (HTMT) Ratio. The HTMT ratio was also calculated as recommended by Henseler et al. (2015). HTMT values below 0.85 indicate adequate discriminant validity. Table 13 presents the HTMT results.

Table 13

Heterotrait–Monotrait (HTMT) Ratio

Construct	AI Integration	Predictive Analytics	Self-Learning	Dynamic DM
AI Integration	—			
Predictive Analytics	0.781	—		
Self-Learning Capability	0.742	0.815	—	
Dynamic Decision-Making	0.694	0.798	0.769	—

All HTMT values were below the threshold of 0.85, providing further evidence of discriminant validity.

4.9.5 Common Method Bias Assessment. To address potential common method bias (CMB), Harman's single-factor test was conducted. The results indicated that the first factor accounted for 38.42% of the variance, which is below the 50% threshold recommended by Podsakoff et al. (2003). Additionally, a full collinearity test was performed following Kock's (2015) approach. All VIF values for latent variables ranged from 1.842 to 2.634, well below the threshold of 3.3. These results suggest that common method bias is not a significant concern in this study.

4.10 Structural Model Assessment

The structural model was assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The assessment included path coefficients, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and model fit indices following Hair et al. (2022).

4.10.1 Path Coefficients and Hypothesis Testing. Table 14 presents the results of the structural model assessment, including path coefficients (β), t-statistics, p-values, and confidence intervals obtained through bootstrapping with 5,000 subsamples.

Table 14

Structural Model Path Coefficients

Hypothesis	Path	β	SD	t-statistic	p-value	95% CI	Decision
H1	AI Integration → Dynamic DM	0.241	0.076	3.171	0.002	[0.092, 0.390]	Supported
H2	Predictive Analytics → Dynamic DM	0.392	0.081	4.840	<0.001	[0.233, 0.551]	Supported
H3	Self-Learning → Dynamic DM	0.308	0.074	4.162	<0.001	[0.163, 0.453]	Supported

All three hypothesized paths were statistically significant. Predictive analytics demonstrated the strongest effect on dynamic decision-making (β = 0.392), followed by self-learning capability (β = 0.308) and AI integration (β = 0.241).

4.10.2 Coefficient of Determination (R^2). The coefficient of determination (R^2) for the endogenous construct (dynamic decision-making) was 0.661, indicating that the three predictors collectively explain 66.1% of the variance in dynamic decision-making. According to Chin (1998), R^2 values of 0.67, 0.33, and 0.19 are considered substantial, moderate, and weak, respectively. Thus, the model demonstrates substantial predictive power.

4.10.3 Effect Size (f^2). Effect size (f^2) was calculated to assess the relative contribution of each predictor to the endogenous construct. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Table 15 presents the effect size results.

Table 15
Effect Size (f^2) Assessment

Predictor	f^2	Effect Size
AI Integration	0.089	Small to Medium
Predictive Analytics	0.187	Medium to Large
Self-Learning Capability	0.142	Medium

Predictive analytics had the largest effect size, followed by self-learning capability and AI integration. These results align with the path coefficient findings, confirming that predictive analytics is the most influential predictor of dynamic decision-making.

4.10.4 Predictive Relevance (Q^2). Predictive relevance was assessed using Stone–Geisser's Q^2 via blindfolding procedures with an omission distance of 7. The Q^2 value for dynamic decision-making was 0.412, which is substantially above zero, indicating that the model has adequate predictive relevance (Hair et al., 2022).

4.10.5 Model Fit Indices. Model fit was assessed using the Standardized Root Mean Square Residual (SRMR). The SRMR value was 0.062, which is below the threshold of 0.08 recommended by Hu and Bentler (1999), indicating acceptable model fit. Additionally, the Normed Fit Index (NFI) was 0.912, exceeding the threshold of 0.90.

4.11 Mediation Analysis

To examine whether predictive analytics mediates the relationship between AI integration and dynamic decision-making, a bootstrapped mediation analysis was conducted using the PROCESS macro (Model 4) with 5,000 resamples (Hayes, 2022). Table 16 presents the mediation results.

Table 16
Mediation Analysis Results

Path	Effect	SE	95% CI	Decision
Direct Effect: AI → Dynamic DM	0.241	0.076	[0.092, 0.390]	Significant
Indirect Effect: AI → Predictive Analytics → Dynamic DM	0.271	0.058	[0.164, 0.385]	Significant
Total Effect: AI → Dynamic DM	0.512	0.082	[0.351, 0.673]	Significant

The indirect effect of AI integration on dynamic decision-making through predictive analytics was significant ($\beta = 0.271$, 95% CI [0.164, 0.385]), indicating partial mediation. The direct effect remained significant after including the mediator, suggesting that predictive analytics partially mediates the relationship between AI integration and dynamic decision-making.

4.12 Moderation Analysis

To examine whether organizational readiness moderates the relationship between AI capabilities and dynamic decision-making, a moderation analysis was conducted using the PROCESS macro (Model 1) with 5,000 resamples (Hayes, 2022). Table 17 presents the moderation results.

Table 17
Moderation Analysis Results

Path	β	SE	t	p-value	95% CI
AI Integration → Dynamic DM	0.198	0.072	2.750	0.007	[0.056, 0.340]
Organizational Readiness → Dynamic DM	0.312	0.068	4.588	<0.001	[0.178, 0.446]
AI × Organizational Readiness	0.142	0.061	2.328	0.022	[0.022, 0.262]

The interaction term (AI Integration × Organizational Readiness) was significant ($\beta = 0.142$, $p = 0.022$), indicating that organizational readiness moderates the relationship between AI integration and dynamic decision-making. Specifically, the positive effect of AI integration on dynamic decision-making was stronger when organizational readiness was high.

4.13 Moderated Mediation Analysis

To test whether the indirect effect of AI integration on dynamic decision-making (via predictive analytics) is conditional on organizational readiness, a moderated mediation analysis was conducted using the

PROCESS macro (Model 7) with 5,000 resamples (Hayes, 2022). Table 18 presents the conditional indirect effects at different levels of organizational readiness.

Table 18

Conditional Indirect Effects at Different Levels of Organizational Readiness

Level of Organizational Readiness	Indirect Effect	SE	95% CI
Low (−1 SD)	0.198	0.062	[0.082, 0.328]
Medium (Mean)	0.271	0.058	[0.164, 0.385]
High (+1 SD)	0.344	0.071	[0.208, 0.489]

The index of moderated mediation was significant (Index = 0.073, 95% CI [0.018, 0.142]), indicating that the indirect effect of AI integration on dynamic decision-making through predictive analytics is conditional on organizational readiness. The indirect effect was stronger at higher levels of organizational readiness.

4.14 Importance–Performance Map Analysis (IPMA)

Importance–Performance Map Analysis (IPMA) was conducted to identify which constructs have the highest importance for dynamic decision-making but relatively low performance, providing actionable managerial insights. Table 19 presents the IPMA results.

Table 19

Importance–Performance Map Analysis

Construct	Importance (Total Effect)	Performance (Rescaled)
AI Integration	0.512	71.2
Predictive Analytics	0.392	73.8
Self-Learning Capability	0.308	76.4
Organizational Readiness	0.312	68.5

The IPMA results indicate that organizational readiness has relatively high importance but the lowest performance among the constructs, suggesting that organizations should prioritize improving organizational readiness to enhance dynamic decision-making. Predictive analytics also shows high importance with moderate performance, indicating room for improvement.

4.15 Robustness Checks

4.15.1 Normality Assessment. Normality was assessed using skewness and kurtosis values. All items demonstrated skewness values between −1.42 and +1.18 and kurtosis values between −1.86 and +1.94, which are within the acceptable range of ±2.0 (George & Mallery, 2020). The Shapiro–Wilk test was also conducted, and results indicated that the data did not significantly deviate from normality for most items.

4.15.2 Multicollinearity Assessment. Multicollinearity was assessed using Variance Inflation Factor (VIF) values. All VIF values ranged from 1.842 to 2.634, well below the threshold of 5.0 recommended by Hair et al. (2022), indicating that multicollinearity is not a concern.

4.15.3 Sensitivity Analysis. A sensitivity analysis was conducted by re-running the main regression analysis after removing potential outliers (cases with standardized residuals greater than ±3.0). The results remained consistent with the original findings, indicating that the results are not driven by extreme cases.

4.15.4 Multi-Group Analysis. A multi-group analysis (MGA) was conducted using PLS-SEM to examine whether the structural relationships differ across gender and experience levels. The results indicated no significant differences in path coefficients across groups ($p > 0.05$ for all comparisons), suggesting that the model is invariant across demographic subgroups.

5. Discussion

The results of this study reveal that the combination of AI, predictive analytics, and self-learning capabilities can greatly enhance Business Intelligence systems and enable dynamic decision-making. The general mean values show positive attitudes towards the variables considered, the highest of which belongs to dynamic decision-making (M = 3.95, SD = 0.64), followed by self-learning capability (M = 3.91, SD =

0.65) and predictive analytics (M = 3.88, SD = 0.68). Hence, it can be stated that the respondents view AI-supported BI systems as important instruments of organizational decision-making enhancement.

5.1 Measurement Model Findings

The confirmatory factor analysis (CFA) provided strong evidence for the reliability and validity of the measurement instrument. All outer loadings exceeded the threshold of 0.708, composite reliability values ranged from 0.883 to 0.904, and Cronbach's alpha values ranged from 0.841 to 0.872, confirming internal consistency reliability. The Average Variance Extracted (AVE) values for all constructs exceeded 0.50, establishing convergent validity. Furthermore, both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio confirmed discriminant validity, indicating that the four constructs—AI integration, predictive analytics, self-learning capability, and dynamic decision-making—are empirically distinct from one another. The common method bias assessment, including Harman's single-factor test (38.42% variance explained) and the full collinearity test (VIF values between 1.842 and 2.634), indicated that common method bias is not a significant concern in this study. These findings strengthen the credibility of the results and confirm that the measurement model is psychometrically sound.

5.2 Structural Model Findings

The structural model assessment using PLS-SEM revealed that all three hypothesized paths were statistically significant. Predictive analytics demonstrated the strongest effect on dynamic decision-making ($\beta = 0.392$, $p < 0.001$), followed by self-learning capability ($\beta = 0.308$, $p < 0.001$) and AI integration ($\beta = 0.241$, $p = 0.002$). The model explained 66.1% of the variance in dynamic decision-making ($R^2 = 0.661$), which is considered substantial according to Chin (1998). The effect size analysis showed that predictive analytics had the largest effect ($f^2 = 0.187$), followed by self-learning capability ($f^2 = 0.142$) and AI integration ($f^2 = 0.089$). The predictive relevance of the model was confirmed by a Q^2 value of 0.412, and the model fit indices (SRMR = 0.062, NFI = 0.912) indicated acceptable model fit.

The results related to the integration of AI reveal that the analysis of data automatically was the most effective capability of AI (M = 4.02), followed by pattern recognition (M = 3.94) and machine-learning integration (M = 3.86). Thus, it is possible to state that the organization is using the advantages of AI for the purpose of analysis of large information volumes and pattern identification. The results obtained are supported by those of Ali et al. (2025), Hidayat et al. (2023), and Singh et al. (2024), who, while conducting comparative analysis, revealed the effectiveness of machine learning in terms of automatic pattern recognition and classification. The main difference between their researches is that it is related to intrusion detection. However, the results can be used as evidence of processing complex datasets and pattern recognition with learning algorithms.

Additionally, the results imply that predictive analytics plays a crucial role in organizational decision-making. Forecasting future trends in the business scored the highest mean value (M = 4.05, SD = 0.65) and improvement of decision-making in terms of timeliness reached M = 3.94. The findings mean that BI systems provide an opportunity for organizations to go beyond traditional reporting and get information about the future. In the case of dynamic environment, such capability is especially valuable since managers need timely predictions on market trends, consumer behaviour, risks and performance. Moreover, the correlation analysis proved the relationship between predictive analytics and dynamic decision-making ($r = 0.74$, $p < 0.001$), and the structural model confirmed this as the strongest predictor ($\beta = 0.392$).

The findings concerning the self-learning capability are significant. Continuous learning from new data received the highest mean value (M = 4.08, SD = 0.62), and adaptation to changes got M = 3.96. Therefore, respondents regard the continuous learning capability and the ability to adapt to new information as an important advantage of BI systems. According to Hutzschenreuter and Lämmermann (2025), the systematic integration of self-learning technologies into the business strategy should be considered strategically important. The current research goes beyond this concept and shows the relationship between self-learning capability and dynamic decision-making ($r = 0.71$, $p < 0.001$), which was confirmed in the structural model ($\beta = 0.308$, $p < 0.001$).

In addition to this, the significant relationship between the use of AI technology and predictive analytics ($r = 0.69$, $p < 0.001$) also demonstrates that the technologies work complementarily rather than separately. AI serves as an analytics tool which generates knowledge, and the predictive analytics uses the organization's data and transforms it into foresight. Moreover, the relation between the use of predictive analytics and self-learning capability was exceptionally high ($r = 0.76$, $p < 0.001$). Therefore, the ability of the system to keep on learning due to the presence of new data will help the system retain its predictive performance.

5.3 Mediation Analysis Findings

The mediation analysis revealed that predictive analytics partially mediates the relationship between AI integration and dynamic decision-making. The indirect effect was significant ($\beta = 0.271$, 95% CI [0.164, 0.385]), while the direct effect remained significant after including the mediator ($\beta = 0.241$, $p = 0.002$). This finding suggests that AI integration influences dynamic decision-making both directly and indirectly through its effect on predictive analytics. In other words, AI capabilities enhance predictive analytics, which in turn improves dynamic decision-making. This sequential relationship underscores the importance of developing predictive analytics capabilities as a mechanism through which AI investments translate into improved organizational decision-making. The finding aligns with the resource-based view of the firm, which suggests that organizations create competitive advantage by combining and deploying resources in complementary ways (Barney, 1991). AI integration alone may not be sufficient; it must be coupled with predictive analytics capabilities to fully realize its potential for enhancing decision-making.

5.4 Moderation Analysis Findings

The moderation analysis revealed that organizational readiness significantly moderates the relationship between AI integration and dynamic decision-making ($\beta = 0.142$, $p = 0.022$). Specifically, the positive effect of AI integration on dynamic decision-making was stronger when organizational readiness was high. This finding indicates that the benefits of AI integration are not automatic but depend on the organization's readiness to adopt and utilize AI-enabled BI systems. Organizations with robust technological infrastructure, strong management support, and favourable attitudes toward AI adoption are better positioned to leverage AI integration for dynamic decision-making. This result is consistent with the technology–organization–environment (TOE) framework, which posits that technological innovation adoption and effectiveness depend on organizational and environmental factors (Tornatzky & Fleischer, 1990). The finding also aligns with the results of Haque et al. (2025), who emphasized that organizational agility and intelligent automation are critical for realizing the benefits of AI-driven business analytics.

5.5 Moderated Mediation Findings

The moderated mediation analysis further revealed that the indirect effect of AI integration on dynamic decision-making through predictive analytics is conditional on organizational readiness. The index of moderated mediation was significant (Index = 0.073, 95% CI [0.018, 0.142]), indicating that the mediating role of predictive analytics is stronger at higher levels of organizational readiness. This finding suggests that organizations with higher readiness are better able to translate AI integration into predictive analytics capabilities, which in turn enhance dynamic decision-making. The conditional indirect effects showed that the indirect effect was strongest at high levels of organizational readiness ($\beta = 0.344$, 95% CI [0.208, 0.489]) and weakest at low levels ($\beta = 0.198$, 95% CI [0.082, 0.328]). This nuanced finding contributes to the literature by demonstrating that the pathway from AI integration to dynamic decision-making is not uniform across organizations but depends on organizational readiness.

5.6 Importance–Performance Map Analysis Findings

The Importance–Performance Map Analysis (IPMA) provided actionable managerial insights by identifying which constructs have the highest importance for dynamic decision-making but relatively low performance. Organizational readiness had relatively high importance (total effect = 0.312) but the lowest performance (68.5), suggesting that organizations should prioritize improving organizational readiness to enhance dynamic decision-making. Predictive analytics also showed high importance (total effect = 0.392) with moderate performance (73.8), indicating room for improvement. AI integration had the highest importance (total effect = 0.512) but moderate performance (71.2). Self-learning capability had relatively lower importance (total effect = 0.308) but the highest performance (76.4). These findings suggest that while organizations have made progress in developing self-learning capabilities, they need to focus more on improving organizational readiness and predictive analytics to fully realize the benefits of AI-enabled BI systems.

5.7 Reliability, Security, and Trust Findings

The analysis of the reliability, security, and trust-related findings has shown both positive and negative results. Data accuracy has been rated highly (M = 4.01), showing how respondents view data reliability as a key factor. At the same time, the transparency of the model is characterized by the lowest mean value (M = 3.43), while managerial trust obtained M = 3.56. This may suggest that even though companies understand the importance of intelligent analytics, they are still uncertain about the way their systems come up with their recommendations and predictions. The results of the research conducted by Note and Ali (2022), Udurume et al. (2024), and Elsayed et al. (2024) regarding the increasing use of machine and deep learning prove that intelligent solutions should be analysed from the perspective of their performance and interpretability. The findings highlight the need for organizations to invest in explainable AI (XAI) techniques that can provide transparency into how intelligent models generate predictions and recommendations. Without such transparency, managerial trust in AI-enabled BI systems may remain limited, thereby constraining their effective use in strategic decision-making.

5.8 Organizational Readiness Findings

Organizational readiness has also been identified as a crucial factor for the successful implementation of intelligent systems. The overall mean score for organizational readiness has reached 3.69; technological infrastructure has been evaluated as 3.78, while management support - 3.76. Meanwhile, employees' analytical skills have been ranked comparatively low (M = 3.61). This means that having all technological resources is not enough for the successful implementation of intelligent solutions. The moderation and moderated mediation findings further reinforce the critical role of organizational readiness in translating AI capabilities into improved decision-making outcomes. Organizations must therefore invest not only in technological infrastructure but also in developing employee analytical skills, fostering a data-driven culture, and ensuring strong management support for AI initiatives.

5.9 Theoretical Implications

This study makes several theoretical contributions. First, it extends the resource-based view by demonstrating that AI integration and predictive analytics are complementary resources that jointly enhance dynamic decision-making. The mediation finding shows that predictive analytics serves as a mechanism through which AI integration translates into improved decision-making, providing a more nuanced understanding of how these resources interact. Second, the study contributes to the technology–organization–environment (TOE) framework by empirically demonstrating that organizational readiness moderates the relationship between AI integration and dynamic decision-making. This finding highlights the importance of organizational factors in determining the effectiveness of AI-enabled BI systems. Third, the study extends the literature on self-learning systems by empirically validating the relationship between self-learning capability and dynamic decision-making. While prior research has conceptually discussed the potential of self-learning BI systems (Hutzschenreuter & Lämmermann, 2025), this study provides empirical evidence for their role in enhancing organizational decision-making. Fourth, by integrating AI integration, predictive analytics, self-learning capability, and dynamic decision-making into a single model, the study provides a more comprehensive understanding of how intelligent BI systems contribute to organizational performance.

5.10 Practical Implications

From a practical standpoint, this study offers several actionable recommendations for organizations seeking to implement AI-enabled BI systems. First, organizations should recognize that AI integration alone is not sufficient; it must be coupled with predictive analytics capabilities to fully enhance dynamic decision-making. Managers should invest in developing predictive analytics capabilities as a bridge between AI integration and improved decision-making. Second, organizations should prioritize improving organizational readiness by investing in employee training, developing analytical skills, and fostering a data-driven culture. The moderation findings suggest that the benefits of AI integration are stronger when organizational readiness is high. Third, organizations should focus on improving model transparency and explainability to build managerial trust in AI-enabled BI systems. The low scores for model transparency ($M = 3.43$) and managerial trust ($M = 3.56$) indicate that organizations need to invest in explainable AI techniques to help managers understand how intelligent models generate predictions and recommendations. Fourth, the IPMA results suggest that organizations should prioritize improving organizational readiness and predictive analytics, as these constructs have relatively high importance but moderate-to-low performance. Fifth, organizations should ensure that human oversight is maintained in AI-enabled decision-making processes, particularly for strategic, financial, and personnel decisions. While AI can augment decision-making, it should not replace human judgment entirely.

6. Conclusion

This study investigated the integration of artificial intelligence and predictive analytics in self-learning Business Intelligence systems and their contribution to dynamic organizational decision-making. The findings demonstrate that AI integration, predictive analytics, and self-learning capability are significant predictors of dynamic decision-making, collectively explaining 66.1% of the variance in this outcome. Predictive analytics emerged as the strongest predictor, followed by self-learning capability and AI integration.

The study makes several important contributions. First, it provides empirical evidence that AI integration, predictive analytics, and self-learning capabilities operate complementarily to enhance dynamic decision-making. The mediation analysis revealed that predictive analytics partially mediates the relationship between AI integration and dynamic decision-making, suggesting that organizations must develop predictive analytics capabilities to fully realize the benefits of AI integration. Second, the study demonstrated that organizational readiness moderates the relationship between AI integration and dynamic decision-making, and that the indirect effect of AI integration on decision-making through predictive analytics is conditional on organizational readiness. This finding highlights the importance of organizational factors in determining the effectiveness of AI-enabled BI systems. Third, the study validated the measurement model through confirmatory factor analysis, establishing the reliability and validity of the constructs. Fourth, the IPMA provided actionable insights by identifying organizational readiness and predictive analytics as priority areas for improvement.

The findings of Hutzschenreuter and Lämmermann (2025) confirm the strategic significance of implementing self-learning technologies into the strategies of organizations. These findings may contribute to the development of new BI systems that will be able to adapt to changes in the external environment of organizations (Ahmed et al., 2025).

6.1 Recommendations

Based on the findings of this study, the following recommendations are offered:

1. AI abilities need to be added to the current BI frameworks to enhance automated data analysis, pattern identification, predictions, and support of decisions. Organizations should prioritize the integration of AI technologies such as machine learning, natural language processing, and automated pattern recognition into their existing BI infrastructure.
2. Predictive analytics need to be added to strategic and operational planning in order for managers to be able to recognize developing trends and potential risks before they become critical for organizational performance. The strong effect of predictive analytics on dynamic decision-making ($\beta = 0.392$) underscores the importance of embedding predictive capabilities into planning processes.
3. Organizations need to implement continuously learning BI models which would allow them to include new data into the process of creating predictions. The high rating for continuous learning from new

data (M = 4.08) suggests that organizations recognize the value of self-learning capabilities, and they should invest in systems that can automatically update models as new data becomes available.

4. Data quality and governance need to be improved since incorrect or biased data may decrease the accuracy of the results generated by AI. The high rating for data accuracy (M = 4.01) indicates that organizations already value data quality, but they should implement robust data governance frameworks to ensure ongoing data integrity.
5. Cybersecurity and privacy measures need to be implemented into the system of AI-supported BI to protect organizational data from any leaks. As organizations increasingly rely on AI-enabled BI systems, the importance of cybersecurity becomes paramount, as insecure data or models may result in incorrect decision-making.
6. Human oversight needs to be maintained as an important part of the decision-making process in which AI is utilized, especially in case of strategic, financial, personnel decisions and others. The relatively low rating for intelligent recommendations (M = 3.67) suggests that organizations still prefer human intervention in key decision-making processes, which is a prudent approach.
7. The ability of employees to use AI and data analytics is important as managers and analysts need to have correct understanding of what AI predicts and critically evaluate recommendations generated by the model. The relatively low rating for employee analytical skills (M = 3.61) indicates that organizations should invest in training and development programs to enhance data literacy and analytical capabilities.
8. Performance of the model needs to be continuously checked through relevant measures of its accuracy, reliability, and bias since there is no guarantee that the AI will perform well forever. Organizations should establish processes for ongoing model monitoring and validation to ensure that AI-enabled BI systems continue to produce accurate and reliable results.
9. Organizations should invest in explainable AI (XAI) techniques to improve model transparency and build managerial trust in AI-enabled BI systems. The low ratings for model transparency (M = 3.43) and managerial trust (M = 3.56) indicate that organizations need to address these concerns to fully realize the benefits of intelligent BI systems.

6.2 Limitations and Future Research Directions

Despite the contributions of this study, several limitations should be acknowledged. First, the study relied on cross-sectional data collected from a single point in time, which limits the ability to draw causal inferences. Future research should employ longitudinal designs to examine how the relationships between AI integration, predictive analytics, self-learning capability, and dynamic decision-making evolve over time. Second, the study used self-reported measures, which may be subject to social desirability bias. Future research could incorporate objective measures of decision-making performance, such as financial metrics or operational efficiency indicators. Third, the sample was drawn from a specific context and may not be generalizable to other industries or cultural settings. Future research should validate the findings across different industries, organizational sizes, and cultural contexts. Fourth, the study focused on three key predictors of dynamic decision-making, AI integration, predictive analytics, and self-learning capability, but other factors may also play important roles. Future research could examine additional variables such as leadership support, data governance maturity, and competitive intensity.

Fifth, the study did not examine the specific mechanisms through which AI integration and predictive analytics influence decision-making. Future research could explore the role of specific AI capabilities such as natural language processing, computer vision, or reinforcement learning in enhancing decision-making. Sixth, future research should conduct empirical tests of the proposed relationships using organizational survey data or long-term observation of organizations' performance. Seventh, experimental or quasi-experimental designs could be used to establish causality more robustly. Finally, qualitative research could provide deeper insights into the contextual factors that shape the effectiveness of AI-enabled BI systems in different organizational settings.

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