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Original Article

Enhancing Decision-Making Effectiveness: Unleashing the Synergy of Artificial Intelligence and Business Intelligence in Modern Enterprises

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ABSTRACT

This study explores the transformative potential of integrating artificial intelligence with business intelligence to enhance decision-making effectiveness in modern enterprises. Using a quantitative approach, the research focuses on the case of Pakistan Telecommunication Company Limited, a leading internet services provider in Pakistan, to examine the synergistic relationship between artificial and BI. Key factors analyzed include artificial intelligence integration, business intelligence tool usage, and data processing speed, with findings indicating that these variables collectively explain a significant 41.2% variance in decision-making effectiveness. The results highlight artificial intelligence's capability to enhance predictive and prescriptive analytics, business intelligence's utility in data visualization, and the critical role of real-time data processing. Recommendations emphasize strategic artificial and business intelligence integration, robust data governance, user training, and ethical considerations to maximize organizational benefits and maintain competitive advantage. This research provides actionable insights for stakeholders and contributes to the growing discourse on artificial and business intelligence integration in business strategy.

Keywords: Artificial intelligence, Business intelligence tools usage, Decision-making, Real-time data analytics

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INTRODUCTION

Decision-making is becoming one of the most complex tasks globally in the new business landscape. Organizations now operate within a rapidly changing environment, characterized by widespread data, new evolutions, and advancements in technology, as well as competitive pressures. For these reasons, organizations have to operate within a rapidly changing environment. (Eboigbe et al., 2023). In response to these challenges, there are several tools in the market, like Artificial Intelligence (AI) and Business Intelligence (BI), that make it easier to access useful information from large databases (Božić, 2024). Due to the potential to change traditional decision-making processes by providing deep, more predictive, and useful data, the integration of AI with BI is considered to be a key area of our research (Badmus et al., 2024)

Business leaders are analyzing traditional decision-making techniques, mostly due to the fluctuations in historical data and descriptive analytics (Tiwari, 2024). The changing business environment is not improved by these traditional methods. For this purpose, predictive and prescriptive analytics are now made possible by AI's extensive machine learning algorithms and data processing powers, which not only offer benefits but also remove all restrictions (Russell & Norvig, 2021). Organizations may achieve new heights of efficiency and innovation by combining the structured analytical capabilities of BI with the computing power of AI (Brynjolfsson & McAfee, 2017).

The ability of AI to process and analyze large amounts of data in real time provides organizations with a competitive edge in this growing business environment. It directly helps in decision-making that turns out to respond effectively and efficiently to the dynamics of the market, preferences of its customers, and operational challenges (Davenport & Ronanki, 2017). For example, companies that work in the retail sector can use AI-enhanced BI tools to keep records of purchasing patterns and optimize inventory management, as a result, ensuring that customer demands are met without overproduction or stocking (Sun et al., 2017). Similarly, in the field of healthcare, applications such as disease outbreak prediction, optimal resource allocation, and improvement in patient outcomes have all gained substantially from AI-driven BI systems (Manyika & James, 2011).

Moreover, AI and BI integration allow for more inclusive and democratized decision-making processes. The traditional BI systems usually required specialized skills in the interpretation of data, where only a limited number of analysts or executives could access such information (Chen et al., 2012; Talaoui & Kohtamäki, 2021). AI, having natural language processing capabilities and consumer-friendly interfaces, brings advanced analytics even to non-specialists. Managers in businesses, frontline workers, and even customers can interact with data-driven insights, which can be seen to promote a culture of data literacy and collaboration (Mah et al., 2022)

Integration of AI and BI is not without its challenges. The technical, ethical, and operational hurdles in realizing the full potential of these technologies have to be negotiated by an organization. Critical success factors influencing the outcomes of AI-BI initiatives are data quality and governance, algorithmic transparency, and user training (Jobin et al., 2019). Proactively addressing such challenges, organizations can build resilient systems that will increase decision-making effectiveness and gain stakeholder confidence (Brynjolfsson & McAfee, 2017).

This research aims to explore the transformative potential of integrating AI and BI within modern firms. In essence, it looks into how this synergy enhances decision effectiveness by analyzing major determining factors, which include data processing speed, functionality of BI tools, and strategic exploitation of AI algorithms. Addressing these important things, therefore, brings an understanding of the mechanisms through which AI and BI are jointly related to better organizational outcomes (Goodfellow et al., 2016).

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Business Intelligence (BI) has evolved right from the beginning. From a simple framework for reporting and basic data visualization, it has grown into advantageous tools that can do all the things, like integration, analysis, and present complex data to enable decision-making (Solanki, 2023). The early BI systems were characterized by their reliance on manual data extraction processes, which caused inaccuracy and delay issues (Negash, 2004). However, increases in computing power, coupled with the power of cloud technologies and data analytics, have given BI more capabilities, including real-time analytics, predictive modeling, and automated insights (Al-Momani, 2024). The systems that are equipped with AI-BI, can process and analyze data coming from different sources, such as IoT devices, social media platforms, and customer feedback channels (Maslak et al., 2021). By using the natural language processing capability of AI, BI tools can also read unstructured text data, which will be flowing from customer reviews to identify queries and emerging issues (Chandar et al., 2019). This improves not only the speed and accuracy of data analysis but also the decision-making process with deeper insights into the data (Chen et al., 2012).

The integration of AI in BI tools is one of the greatest steps in the natural evolution of data analytics. Traditional BI tools have been good at descriptive analytics, that is, summarizing the historical data in order to identify trends and patterns of information. However, AI goes one step further by using data from prescriptive and predictive analytics (Mallikarjuna et al., 2024). By using past data to predict future sales trends, a company may make timely decisions and offer the best tactics to use them successfully (Sun et al., 2017). Similarly, AI-enhanced BI systems enable organizations to process and analyze data from various sources, such as IoT devices, social media platforms, and customer feedback channels. The integration of natural language processing capabilities of AI also allows BI tools to analyze unstructured text data, customer reviews, and identify sentiment (Chandar et al., 2019). Such integration enhances not only the speed and accuracy of data analysis but also the quality of the decision-making process itself by providing much more holistic insights (Chen & Lin, 2021).

Several factors have driven the integration of AI and BI in growing organizations. One of the primary factors is the increasing need for real-time decision-making in evolving business environments (Davenport & Ronanki, 2018.). It helps the organizations to not only process but also analyze real-time data that is essential for the organizations to respond to changing market needs, customer behavior and perceptions, or trends (Sun et al., 2017). Another important factor is the amount of complex data that is transformed by the digital information (Manyika & James, 2011). Businesses are adopting IoT devices, cloud services, and e-commerce platforms through the use of large datasets generated. With the integration of AI-BI tools, this data can be handled and stored, and can extract the information required for the particular decisions (Gandomi & Haider, 2015).

There are a lot of challenges in the integration of AI-BI, as the accuracy and reliability of these tools are highly dependent on the data quality and maintenance, so any negligence in that part would cause wrong decisions (Wixom & Watson, 2010). For the integration of AI-BI tools in organizations, the high cost of applications and maintenance would occur on the company's budget side, and it would be difficult for small and medium-sized companies to implement (Chen & Lin, 2021). Moreover, ethical concerns, which include algorithm bias and data privacy, also make it complex for companies to adopt these tools (Jobin et al., 2019). To mitigate these risks and build trust among stakeholders, the companies must ensure transparency in algorithms (Brynjolfsson & McAfee, 2017). By addressing these challenges, organizations can unlock the full potential of AI-BI integration to drive innovation and improve decision-making effectiveness.

The convergence of Artificial Intelligence (AI) with Business Intelligence (BI) marks a change in how businesses formulate data-inspired strategy. Traditional BI tools have been proving to be of limited use because they are mainly designed for retroactive data analysis and static reporting, but the trends in AI, such as machine learning, natural language processing, and automated intelligence, are going to play a significant role in the development of business intelligence tools (He et al, 2021). This seamless integration allows us to process and analyze enormous data sets quickly and accurately, providing more robust and actionable insights for strategic decision-making (Schmitt, 2023). It not only enhances the existing functions of

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traditional BI but also helps organizations to obtain real-time insights, which is a competitive need to evolve with changing market dynamics (Al-Momani, 2024).

Traditionally, BI is considered a practice of using past data to come up with future strategies. But the complexity of real-time data created inefficiencies or bottlenecks in traditional BI solutions, and they fail to process large volumes of data (Adewusi et al., 2024). Through AI integration, these limitations are addressed, and the complex processes of evaluating data can be automated much faster than before, allowing for heterogeneous data to be interpreted instantaneously. AI can, for example, identify consumer trends by monitoring social media activity and purchase histories, and enable organizations to make immediate and swift decisions (Niu et al., 2021).

As organizations increasingly recognize the value of enhanced predictive analytics, the adoption of BI tools backed by AI growth too. Traditional BI is mostly historical, and it only allows knowing what happened; however, AI can predict trends and, more importantly, how to produce strategic planning with higher accuracy. They even accommodate some different features, such as common-sense search, automatic pattern matching, and similarities of AI-supported BI tools that reveal connections and findings that may not be evident to a human analyst. The combination of these features helps organizations enhance operational efficiency and gain a competitive advantage, rendering AI-BI integration a true weapon for success in the fast-changing business environment (Bonczek et al., 2024).

Bao et al., (2023) explains transitioning from rational to qualitative decision-making strategies based on a human AI synergy, expanding on how AI capabilities can help human decision processes by providing affordances or functions that help human analysis of data (Adewusi et al., 2024) Moreover, as explained by Schmitt (2023), AutoML also appears to democratize advanced analytics by lowering the barrier to entry using machine learning. Schmitt, (2023) uses AutoML as a benchmark to show its automation capability, which provides accessibility to predictive modeling to non-experts, yet highlights a phenomenon very similar to the one (Al-Momani, 2024). AI adoption elevates traditional BI capacity, automation, and accessibility, consequently contributing to BI transformation (Sutherland & Jarrahi, 2018).

In the age of Big Data, enormous datasets challenge traditional analytical methods, and the effectiveness of AI-BI (Adewusi et al., 2024). This is consistent with Bonczek et al. (2018), who point out that this technological breakthrough allows BI to work on a much bigger scale and turn data into information rapidly enough to help organizations predict and seize market opportunities (Artene et al., 2024). The results explain how AI-based tools can read through rich financial data to find the patterns that are crucial to strategic management and help organizations across industries thrive under pressure. Neural networks and predictive analytics tools (Schmitt, 2023) has been successful in analyzing and extracting actionable insights from big financial data and providing guidance for sustainable growth. Finally, Shwedeh (2024) addresses AI-enhanced BI in higher education, mirrors the emphasis on data quality and user readiness as critical factors in adopting and utilizing AI-driven decision support systems (Rahmani et al., 2021). His findings underscore that a structured approach to implementing AI-driven BI systems focused on quality and engagement maximizes decision support in diverse fields.

Artificial intelligence is an important tool as it enhances decision-making by addressing complex and large-scale data processing. The research paper highlights that AI provides a structured technique to analyse and process large amounts of data that is humanly not possible to handle. For example, AI algorithms excel in the processing procedure, which would make it easy to uncover the customer data, and then, after that, it would also help in guiding how to take strategic marketing actions and improve customer satisfaction (Hlatshwayo, 2023). Moreover, AI and human collaboration is one of the most dynamic changes in the working environment, which is termed as ' intelligence expansion ', which means AI works on the analytical part, while human on the other side manages uncertainty and creativity (Jarrahi, 2018). Businesses applying this technique have proved that it improves decision-making and will respond quickly to market changes, and hence support the decision-making effectively (Mishra & Tripathi, 2021).

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AI-BI integrations have created advantages in the market, as the process of complex and large datasets has now become easy to process by using machine learning and advanced computational methods. Regarding that, nowadays companies use real-time analytics using AI tools in BI, which helps them to make more accurate and effective strategies due to the availability of current data (Lee & Yoon, 2021). Another advantage of this integration is that due to the technological advancements in hardware, such as specialized GPUs and the combination with cloud computing, these all helped companies, whether small or medium-sized, to utilize these tools to make informed and faster solutions to the complex data, which, as a result, increases their market responsiveness and efficiency (Golightly et al., 2022).

In addition, it also helps in business operations and makes informed decisions based on automating repetitive tasks and enabling personalization according to the business. The research paper also highlighted the importance that it enables organizations to maintain costs and mitigate risks (Mohapatra, 2019). Industries like supply chain management also took a lot of advantages from this integration by getting reduced lead times as well as better inventory management (Fahimeh & Ali, 2023). The research paper discussed that the company should align its existing infrastructure with the goals that are going to be achieved in the long run. The data privacy and other issues can be handled through strategic planning and a skilled labor force (Mikalef & Gupta, 2021).

BI tools are able to transform raw data into useful information by supporting the strategic decisions of the organization across all departments. The research paper highlights the importance of its effective usage in the market and industry as well (Razzaque, 2021). AI-BI tools, as per the discussion, showed their importance across all the industries, not particularly to some. If we talk about the health industry, these tools are helpful in predictive diagnostics and managing patients more effectively. Due to this, the outcome comes properly, and it also maintains the cost (Lee & Yoon, 2021; Razzaque, 2021).

AI-driven analytics are used in the financial industry for the maintenance of portfolios, tasks of credit risk, and fraud detection as well. Although AI-integrated BI systems also help organizations to maintain their supply chain operations and quality assurance (Fahimeh & Ali, 2023). Whether extensive research on these AI-BI integrations has been conducted in past research. These past studies didn't study the part of their dependencies and how these both influence the effectiveness of decision-making. The research is fulfilling the gaps in the integration of AI-BI in organizations and how the factors of data processing speed and BI adoption tools would better work in precise and effective decision-making.

Resource-Based View

The resource-based view (BRV) theory underpins this study because it posits that organizations drive competitive advantage from effectively utilizing their unique internal resources that are irreplaceable. AI and BI technologies are one of such resources that offer advanced capabilities for data-driven decision making. These tools enhance efficiency, agility, and accuracy that directly align with RBV's emphasis on leveraging resources that meet VRIN criteria. (Barney, 1991) In the context of AI BI integration, valuable resources mean the ability of the technologies to generate valuable content that can directly contribute to attaining competitive advantages for the companies. For instance, AI-driven predictive analytics can forecast market trends, and as a result, proactive decisions can be made. Meanwhile, BI consolidates this data into accessible formats so that actionable strategies can be derived from this useful information.

Rarity adds to the exclusivity of advanced AI and BI systems. Companies that invest in cutting-edge technologies and proprietary algorithms will be differentiated from their rivals, who otherwise depend on traditional methods. This rare ability to process complex data and leverage it in an effective manner amplifies the competitiveness of a firm. Inimitability means that competitors would find it extremely difficult to replicate the smooth integration of AI and BI tools. Customization, proprietary algorithms, and integration with existing systems make these technologies unique to the enterprise and ensure that the competitive advantages will be sustained.

Non-substitutability means there is no replacement of these two AI and BI in modern decision-making. No other technologies offer the same broader scope of capabilities in real-time data processing, predictive

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analytics, and actionable visualization. By doing this, the companies can make their adoption a critical strategic resource for maintaining market leadership. This study has a greater scope that highlights how both AI and BI within the RBV framework work, how these technologies can function as strategic assets that can not only enhance but can also improve effectiveness in decision making by maintaining the long-term competitive advantages. With their integration, the companies can transform their operational processes, enabling organizations to adapt and sustain growth within dynamic environments.

As per the discussion, the potential of AI and BI takes it to a new level of revolution by making more precise decision-making and exploration in research. Past research regarding these tools, AI, and BI neglects their effectiveness in the business world. Moreover, the critical factors such as data processing speed and the proper strategic deployment of BI, were not discussed. These are the gaps identified in the past research that lack in utilizing both technologies. In this research, addressing these gaps to show the potential of the AI-BI integrations to enhance decision-making strategies for companies effectively.

This study is primarily focusing on the case of Pakistan Telecommunication Company Limited (PTCL), which is known leading internet company of Pakistan. The strategies PTCL include the adoption of advanced technologies, such as AI and BI, to make decision-making more optimized. This research aims to show how both AI and BI influence the decision-making processes of the organization and the advantages it creates in the business world. The study is based on the investigation of whether the integration of AI-BI influences the decision-making process with respect to the functionality and performance of the organizations. This includes identifying the different attributes that can enhance the ease of making decisions and the probability of insights being accessible to the decision-makers in different areas of study. (Adewusi et al., 2024). This study aims to evaluate the synergistic relationship between AI and BI in enhancing decision-making effectiveness.

This study is highly relevant as many organizations across the globe have begun to transform their business operations, which is necessary for their organizations to remain competitive and AI-dependent. The results will clarify the technical, operational, and organizational barriers of existing BI systems and aid the creation of an ecosystem of enterprise-wide, robust AI-augmented BI solutions that can enable operational, accurate, and actionable insights in real time. As today's information-based world is getting more dynamic and fast-moving, the need for adaptability becomes crucial in strategic planning and organizational response (Zohuri, 2020).

METHODOLOGY

The population of study is professionals working at PTCL who use AI and BI tools in their process of decision making, i.e., managers, analysts, and IT professionals who are directly engaged in these activities involving AI and BI integration. This study employs a quantitative approach. We made a questionnaire that was structured to gather data from 153 respondents. We opted for the quantitative method because it helps us to effectively measure and establish the relationship between different variables. This is directly in accordance with the positivist research paradigm (Sekaran & Bougie, 2019). The questionnaire is made to capture the respondents' perceptions regarding AI and BI tools and was distributed electronically to ensure greater participation and minimize logistical constraints.

A sample size of 155 respondents was selected using convenience sampling due to resource limitations. According to Hair et al. (2010), a sample size of at least 100 is sufficient for most research studies to ensure statistical power and reliability of results. The sample size was determined considering the economic and time constraints associated with conducting larger-scale surveys. Creswell & Creswell (2018) highlight that researchers often have to adjust their sample size based on the available resources while ensuring it is statistically significant to draw valid conclusions. This approach makes sure that the study remains feasible without compromising its methodological structure.

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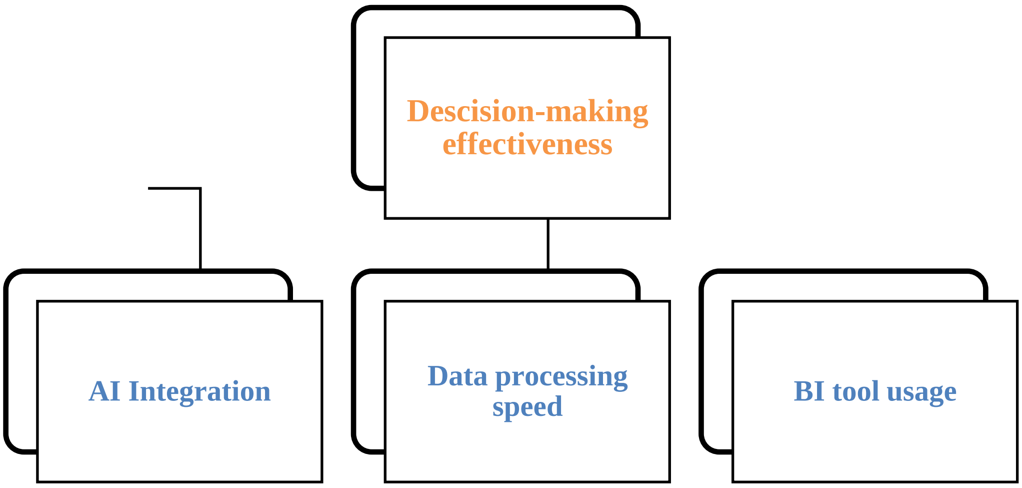
Figure 1: Conceptual Framework



The questionnaire includes the following variables under investigation: Decision Making Effectiveness (DV), AI Integration (IV), BI Tools Usage (IV), and Data Processing Speed (IV). Each section consists of items measured on a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree". The data was collected through Google Forms to maximize reach and ensure accessibility for respondents from the organization. Online data collection was chosen to reduce costs and streamline the process, sticking to recommendations by (Bryman, 2016). Participants were assured of confidentiality and informed that their responses would be used exclusively for academic purposes.

Variables

1. Decision-Making Effectiveness

Decision-making effectiveness is basically the ability of the organization to make decisions that are informed, timely, and accurate, that complement the strategic objectives and operational goals. It consists of dimensions such as speedy decision, accuracy, and the ability to change with circumstances (Davenport & Ronanki, 2018). Effective decision-making can be easily evaluated through measurable outcomes such as improved operational efficiency, enhanced customer satisfaction, and increased profitability (Sun et al., 2017). When we look at the context of AI-BI integration, we see that decision-making effectiveness is significantly enhanced by real-time analytics and predictive analytics, along with automated recommendations (Chen & Lin, 2021).

2. AI Integration

AI integration is the addition of artificial intelligence technology into business processes and systems, especially in BI systems, to enhance their analytical and predictive capabilities. (Brynjolfsson & McAfee, 2017). It involves using AI algorithms such as machine learning and NLP to automate analysis, identify patterns, and provide actionable recommendations. (Goodfellow et al., 2016). AI integration transforms traditional BI tools that are traditional by adding capabilities for predictive and prescriptive analysis, enabling organizations to achieve a competitive advantage by optimizing strategies.

3. BI Tool Usage

BI tools usage refers to the application of BI platforms to analyze, collect, and visualize business data. Effective usage of Business intelligence tools involves alignment with organizational goals, not only the technical capabilities of the system (Wixom & Watson, 2010). Modern BI tools include features such as interactive dashboards and real-time visualization of data and advanced analytics, which support strategic, operational, and tactical decision-making. (Turban et al., 2015). The strategic use of BI tools is necessary to maximize the benefits of AI integration and enhance decision-making effectiveness. (Medeiros et al., 2020)

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4. Data Processing Speed

Data processing speed is the rate at which the organization can collect, analyze, and generate insights on which it can take action. It is one of the most important factors in the success of AI-powered BI tools, as it directly affects the time of decision-making (Manyika & James, 2011). Advancements in machine learning algorithms and computing power have drastically increased the speed of data processing, which enables organizations to handle large data sets effectively and generate real-time insights (Gandomi & Haider, 2015). Faster data processing allows companies to tackle market changes and operational challenges in customer demands (Chen & Lin, 2021)

In addition, we discuss critical questions, such as: How does AI integration affect the effectiveness of decision-making? What is the role of data processing speed and BI tool adoption in enhancing decision outcomes? Can AI-driven BI systems provide sustainable competitive advantages? These questions provide a structured framework for understanding the strategic value of AI-BI integration, offering a novel perspective that emphasizes actionable insights and practical applications.

This study relates and extends RBV by examining AI and BI as strategic resources and their exploitation for the acquisition of a sustainable source of competitive advantage through the leveraged use of distinctive, valuable resources. The study integrates advanced technologies and contributes to the RBV discourse on resource orchestration. It sheds light on how AI-BI systems function as integrated capabilities that go beyond the sum of their parts. The study focuses on data processing, predictive analytics, and decision support, which underscores the strategic significance of intangible, knowledge-based resources, thereby underlining the continued relevance of RBV in the digital economy. The study bridges theoretical constructs with actionable recommendations, demonstrating how RBV can guide organizations in leveraging AI-BI integration to achieve sustainable competitive advantages.

Estimation of Result

The descriptive statistics show the overall mean scores and standard deviations, and, more importantly, the sample size (N=153) in relation to every computed variable.

Table 1: Reliability Analysis

Variables	Cronbach's Alpha	N of Items
Decision-making Effectiveness	0.754 (75.4%)	6
Ai integration	0.884 (88.4%)	6
Business intelligence tool usage	0.736 (73.6%)	5
Data processing speed	0.762 (76.3%)	5
Total	0.907 (90.7%)	22

The reliability according to the above table of reliability analysis. Individual and overall variables' reliability is more than 0.70 or 70%. This makes sure that our data is reliable and fit for further statistical analysis. For the data to be called normal, the data should have a skewness value between -3.58 and 3.58. The value of our skewness is -0.33, which confirms the normality of the data.

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Table 2: Correlation analysis

		Data processing speed	Decision Making effective	AI integration	Business intelligence tools usage
Data processing speed	Pearson Correlation	1			
Decision-Making effectiveness	Pearson Correlation	.519**	1		
AI integration	Pearson Correlation	.550**	.553**	1	
Business intelligence tools usage	Pearson Correlation	.525**	.552**	.621**	1

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation analysis finds a positive and significant correlation between all the variables and decision-making effectiveness. The decision-making effectiveness has a moderate relation with all variables. The AI integration and business intelligence tools usage have the strongest relationship, which reinforces that it is critical in enhancing decision outcomes.

Table 3: Model summary

Model	R	R Square	Adjusted R-Square	Durbin-Watson
1	.642	.412	.400	1.660

Table 4: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	12.732	3	4.244	34.829	<.000
Residual	18.157	149	.122		
Total	30.889	152			

Dependent Variable: Decision-making effectiveness

Predictors: Business intelligence tools usage, Data Processing Speed, AI Integration

The result highlights that change in our independent variables, Business Intelligence Tools Usage (BITU), Data Processing Speed (DPS), and AI integration (AII) affect our dependent variable, Decision Making Effectiveness (DME). The independent variables explain 41.2 % of the variance in (DME), indicating a moderate to strong relationship. While our Durbin-Watson value of 1.660 is in the normal range, it demonstrates that there is no autocorrelation problem and ensures the validity of the regression model. The

F-statistic value is 34.829, and the significance is less than 5 %, which provides approval that the model is suitable.

Table 5: Coefficient

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	1.649	.242		6.803	<.000		
Ai Integration	.196	.065	.255	3.000	.003	.545	1.835
Business intelligence tools usage	.213	.066	.268	3.213	.002	.566	1.767
Data processing speed	.185	.061	.237	3.030	.003	.642	1.557

Dependent Variable: Decision-making effectiveness
Predictors: Business intelligence Tools Usage, Data Processing Speed, AI integration

The Vif Value is less than 2 for all variables, proving that there is no multicollinearity and also supporting the robustness of the model.

Equation estimation

Following is the original equation

$$DME = \beta_0 + \beta_1 BITU + \beta_2 DPS + \beta_3 AII$$

Now we will add the unstandardized coefficients.

$$DME = 1.649 + 0.213BITU + 0.185DPS + 0.196AII$$

Interpretation

- The β_0 Represents the baseline level of decision-making effectiveness when all IVs are zero.
- A one-unit increase in BI tools usage will increase decision-making Effectiveness by .213 units while everything remains constant.
- A one-unit increase in Data processing speed will increase decision-making Effectiveness by .185 units while everything remains constant.
- A one-unit increase in AI integration will increase decision-making Effectiveness by 0.196 units while everything remains constant.

DISCUSSION

Our results reveal that AI integration enhances decision-making effectiveness because of its ability to do predictive and prescriptive analysis. This is directly in alignment with Rahmani et al. (2021) and Schmitt (2023), which says that AI improves the precision and speed of decision-making. Data processing speed emerged as one of the most important factors in influencing decision-making effectiveness. This finding is consistent with Sun et al. (2017), who highlighted that real-time data processing is an important aspect to achieve a competitive advantage. Furthermore, BI tools adoption and user engagement mediated the impact of decision-making outcomes, simulating insights from Adewusi et al. (2024) and Shwedeh (2024). Our regression results clearly show that AI integration, coupled with BI tools usage and enhanced data processing

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speed, collectively explained 41.2 % variance in Decision Making Effectiveness. These findings are similar to Al-Momani (2024) and Collins et al. (2021), who found that the strategic benefit of AI-driven BI systems is in maintaining competitive positioning.

Organizations such as PTCL must allocate resources to developing and acquiring advanced AI-powered BI tools. These tools have capabilities such as predictive and prescriptive analysis, real-time data processing, and decision support, enabling businesses to respond actively to the dynamic market conditions. Organizations should ensure that they are customized to align with the organizational needs, so they ensure maximum impact and user relevance.

Secondly, organizations should enhance data governance and quality management because data quality is an important factor for effective AI BI integration. PTCL must ensure that it implements Robust data governance frameworks so that it maintains data integrity, accuracy, and consistency. In addition to establishing protocols to clean data, validate, and standardize, organizations must adopt practices such as data cataloging and monitoring tools so that they can make sure that the inputs for AI systems are free of biases and reliable, so they do not distort decision-making outcomes.

Organizations should also prioritize user training and development because building a workforce that is skilled in using artificial intelligence and business intelligence tools is important for their successful adoption. Design a training program that is comprehensive so that they can enhance data literacy across all organizational levels. These programs should focus on empowering the employees so that they can interact effectively with artificial intelligence and business intelligence tools, interpret analytical insights, and effectively integrate into decision-making processes so that they can encourage a culture of continuous learning that will further enhance user engagement and tool utilization.

Ethical issues such as algorithmic bias, data privacy, and transparency must be addressed actively. PTCL should adopt AI ethics guidelines so that it can ensure fairness and accountability in decisions that are data-driven. Establishing processes that are transparent for AI operation and implementing a secure mechanism to ensure data privacy. Successful artificial intelligence and business intelligence require a cross-functional collaboration. PTCL must ensure that it fosters communication and alignment between technical teams, the decision makers, and end users so that it can ensure that the technology addresses real-world business challenges. Establishing a cross-departmental task force or committee that oversees the artificial intelligence and business intelligence implementation can enhance the synergy between technology and business objectives and also streamline operations.

CONCLUSION

We have studied PTCL to examine the synergy between AI and BI. Our results showed that integrating AI into BI tools significantly enhanced the decision-making effectiveness of the organization. The correlation between artificial intelligence integration, BI tools usage, and data processing speed highlights how they are synergistic in improving the decision-making effectiveness of the organization. AI capability in their prescriptive and predictive analysis, coupled with the business intelligence tools, makes decision-making efficient, timely, and accurate. The regression analysis further showed us that there is a 41.2% variance of the independent variable in decision-making effectiveness.

DECLARATIONS

Consent to participate: Written consent had been obtained. All methods were performed following the relevant guidelines and regulations.
Availability of Data and Materials: Data will be made available upon request. The corresponding author will submit all dataset files.
Competing interests: None
Funding: No funding source involved

AUTHORS' CONTRIBUTIONS

AS: Concept and design of study, critical intellectual input.
AS: Acquisition and analysis of data, drafting of the manuscript, and critical intellectual input.
FI: Acquisition of data, drafting of the manuscript.
The authors had read and approved the final manuscript.

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