

Effects of Business Intelligence Adoption on Decision-Making Effectiveness in Afghan SMEs: Evidence from Khost Province

Murad Ali Ziarmal^{1*}, Akmal Nasir Amiri¹, Gulwali Mohammadzai² and Sayedrahman Zeerak³

¹Senior Teaching Assistant, Business Administration Department, Economics Faculty, Shaikh Zayed University, Khost Afghanistan

²Senior Teaching Assistant, Banking and Finance Department, Economics Faculty, Shaikh Zayed University, Khost Afghanistan

³Teaching Assistant, Business Administration Department, Economics Faculty, Shaikh Zayed University, Khost Afghanistan

*Corresponding author Email: ziarmal60@gmail.com

DOI: 10.64505/tijss/v02issue01/0030

Article Info:

Received:

20/06/ 2026

Revised:

25/07 / 2026

Accepted:

10 /08 2026

Published:

15/08 / 2026

ABSTRACT

Business intelligence (BI) system is a crucial helper that enables SMEs to improve the effectiveness of decision-making. Despite they utilize their experience in decision-making processes. And empirical evidence on the effects of business intelligence on decision-making in Afghanistan remains limited. The purpose of this study is to explore the relationship between business intelligence and decision-making effectiveness in SMEs which operate in Khost province. The primary data were collected through a structured questionnaire which was distributed among 384 top/middle level managers and data analyst employees of SMEs in Khost province. A simple random sample technique is used. A total of 379 questionnaires were returned, 16 were invalid, eliminated from analysis, and 363 were valid, which were analyzed using SPSS and SmartPLSv.4.1.1.8. PLS_SEM technique is employed to test the proposed hypotheses. The finding appeared that BI usage positively and significantly influences decision-making, with a path coefficient ($\beta=0.278$, $p=0.000$), and information quality demonstrated a stronger positive effect on decision-making with ($\beta=0.691$, $p=0.000$) path coefficient. The finding indicates if SMEs effectively utilize business intelligence systems, they can improve decision-making effectiveness. This study contributes practically by providing insights for SMEs managers regarding the importance of digital transformation and BI adoption, theoretically by the extending Resource Based View theory within the context of Afghan SMEs. The study recommends SMEs to invest in BI technologies to strengthen their decisions through accurate, timely and valuable information.

KEYWORDS: Business Intelligence, Decision-Making, Information Quality, PLS-SEM, Resource-Based View, SMEs

1. INTRODUCTION

Effective decision-making is the most critical managerial function that influences organizational performance. In today's volatile and highly competitive business environment, managers are expected to make decisions based on accurate, timely, and relevant information rather than relying solely on personal experience. Business intelligence has emerged as an important technological capability to enhance decision-making effectiveness by integrating organizational data, transforming it into meaningful information, and providing analytical insights that support strategic planning and operational improvements (Teresa Guarda, 2013). Therefore, the value of BI is not associated with the introduction of technology; it depends on the extent to which firms can use BI information to improve decision-making effectiveness.

International research suggests that BI can enhance decision-making effectiveness. Kamali (2009) emphasized that organizations can create value when they are capable of converting raw data into useful intelligence that guides managerial actions. Similarly, Kahaner (1997) argued that intelligence is information that has been filtered, analyzed, and transformed into actionable knowledge, emphasizing that information only creates value when it supports effective organizational decisions. Therefore, the ability of SMEs to adopt business intelligence (BI) technologies can significantly improve the quality, speed, and effectiveness of managerial decision-making, and enable firms to respond more effectively to market dynamics and customer demands (Kamali, 2009).

Regardless of the popularity and benefits of implementing business intelligence systems introduced in the academic field, consequently, many SMEs continue to rely primarily on managers' personal experience instead of data-driven decision-making processes. Such practices limit organizational responsiveness and reduce the ability of firms to achieve sustainable competitive performance in increasingly dynamic markets.

Although previous studies have demonstrated that business intelligence positively influences organizational performance, decision-making, and competitive advantage. Existing literature has predominantly focused on large organizations and firms operating in developed economies (M.Olszak, 2014). Comparatively, little empirical evidence is available regarding the adoption of BI within SMEs, particularly in developing countries such as Afghanistan. Moreover, while previous research has extensively examined the relationship between business intelligence and competitive advantage (Chen, 2012; Eidizadeh Rosa, 2017; Sümeyye Öztürk, 2021), fewer studies have investigated how business intelligence improves organizational performance through managerial decision-making. Titik Kusmantini et al. (2021) further suggested that future research should examine additional mediating mechanisms because the direct effect of business intelligence may be weaker than its indirect influence through organizational capabilities. These observations indicate a clear research gap

regarding the role of decision-making in explaining how business intelligence (BI) creates value for SMEs operating in resource-constrained environments such as Afghanistan Khost province (Titik Kusmantini1, 2021).

The aim of this study is to explore the effects of BI adoption and decision-making effectiveness. Empirical evidence from Khost province, this study provides evidence that business intelligence represents a meaningful mechanism to improve the accuracy, quality, timeliness, and effectiveness of decisions in a resource-constrained business environment.

1.1 Problem Statement

Small and medium scale enterprises (SMEs) contribute significantly to development, job creation and to the growth of the private sector. But, in developing countries, SMEs are often constrained by a lack of resources, technology, and information, which can have a negative impact on managerial decision-making (World Bank, 2024; UNDP, 2026).

Business Intelligence (BI) offers organizations tools to gather, analyze and transform business information into valuable information for better decision-making. Previous research has demonstrated that BI adoption and information quality can positively influence managerial decision-making processes, and organizational performance (Bhatiasavi & Naglis, 2020; Ragazou et al., 2023). But, there is still little known about the use of BI in SMEs in Afghanistan.

Specifically, there is a lack of evidence in the perceptions of SMEs in Khost Province on the impact of BI adoption and the quality of information on the effectiveness of decision-making in the context of SMEs. This gap restricts SME managers and policymakers from gaining practical awareness about the value of BI to enhance them in decision-making. Hence, the object of this study is to analyze the impact of BI adoption and information quality on the effectiveness of the decision-making process of SMEs in Khost Province, Afghanistan and to suggest recommendations for better utilization of BI in the decision-making process of SMEs in Khost Province, Afghanistan.

1.2 Objectives of the study

The aim of this study is to address this gap by investigating the effects of business intelligence adoption on the decision-making effectiveness of SMEs, and the specific objectives of the study are:

- To Examine the Role of Business Intelligence in Improving Decision-Making in SMEs.
- To provide recommendations for enhancing the role of BI in improving competitive advantage

1.3 Questions of the study

These questions are intended to be answered.

1. How can business intelligence (BI) adoption effectively strengthen the decision-making of SMEs?
2. What recommendations can be provided to enhance the role of BI in improving decision-making?

1.4 Hypotheses of the study

H1: The use of business intelligence has a positive and significant effect on decision-making.

H2: Information Quality has a positive and significant effect on decision-making.

1.5 Significance of study

The current study contributes with practical business management and academic knowledge and also provides evidence from a developing country context, such as Afghanistan. The findings of the study would help SMEs managers, policymakers and those who engage in technology to understand how business intelligence (BI) systems enhance competitiveness and may encourage digital transformation within SMEs, and also provide insights into the role of business intelligence (BI) in supporting the decision-making process.

This study is theoretically grounded in the Resource-Based View (RBV), which argues that organizations achieve sustainable competitive advantage through valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). From this perspective, business intelligence can be considered a strategic organizational resource that enables firms to acquire, process, and exploit information more effectively than competitors. Previous studies have widely applied Resource Based View to explain the strategic value of business intelligence (BI) and organizational capabilities (Daniel Mbima, F. K, 2022; Vincent English, 2018; Yucheng Zhang, 2021).

Accordingly, this study investigates the adoption of business intelligence (BI) and its influence on decision-making effectiveness among SMEs in Afghanistan. Specifically, the study examines how business intelligence (BI) contributes to decision-making and provides empirical evidence from SMEs operating in Khost Province. By addressing the limited empirical evidence available from developing countries, this research contributes to the growing business intelligence literature while offering practical implications for SMEs managers, policymakers, and technology experts seeking to strengthen organizational decision-making through digital transformation and information-driven management practices.

2. LITERATURE REVIEW

2.1 Business Intelligence

The process of transforming data into intelligence for use in strategic decision-making is known as business intelligence. Business intelligence (BI) systems can be used by organizations to gather and process data, forward results to pertinent departments, support decision-making, and predict future occurrences. Business intelligence

(BI) enables executives to make prompt and appropriate decisions (Sümeyye Öztürk, 2021). Additionally, business intelligence (BI) refers to the integration and analysis of an organization's data resources to support decision-making. Business intelligence (BI) is truly growing more and more significant in a number of business kinds since information has been acknowledged as a company's most valuable asset. Similar to gold or money, data is today a new type of economic asset (Carlos Andrés Tavera Romero, 2021).

Three categories of business intelligence (BI) exist: 1. BI that is operational; 2. BI that is situational; and 3. BI that is self-service (Sael, 2017). The capacity to find, use, apply, and safeguard (SI, UI, IA, and DS) vital business information is one of the main characteristics of business intelligence (BI) that enhances its performance (Tirno, 2024). Data acquisition, data management, data analytics, data reporting, and integration of business intelligence with the decision-making process are the main components of business intelligence (BI) in small and medium-sized enterprises (SMEs) (Blessing, 2024). The efficacy of BI systems is heavily reliant on these three essential components: 1. Data acquisition (Extract transform load (ETL)) 2. Data storage (data warehouse) 3. Data analytics (Online analytical processing (OLAP)) (Venkatakrishnan, 2020).

Businesses can anticipate and adapt to changes in the market thanks to business intelligence (BI). In order to remain competitive in a corporate climate that is evolving quickly, SMEs should strategically use business intelligence (BI) (Blessing, 2024).

2.2 Decision-Making

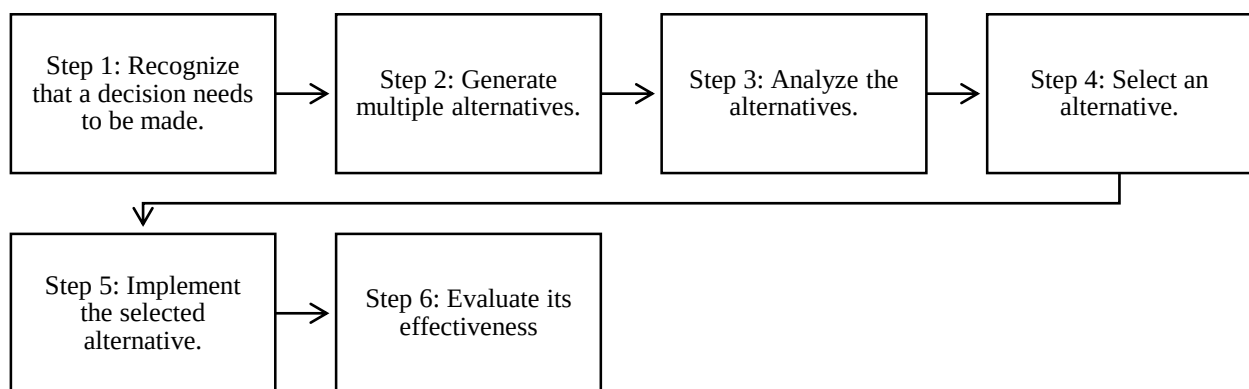
Making a decision is the process of evaluating several options and selecting one. Making decisions is essential to an organization's functioning. In light of this, "decision-making is the study of identifying and selecting alternatives based on the decision-maker's values and preferences." According to Lahbi (2018), having a variety of options is necessary while making a decision. Parkin (1996) divided the decision-making literature into three categories. The first group includes the amount of data that describes the choice theories supporting the DMP. The second group comes from psychological research, which includes models of decision-based behavior. It thereby clarifies the limitations of the human mind in the DMP. The third category describes the DMP in organizations (Lahbi, 2018; Parkin, 1996).

Decision-making is one of the most critical managerial responsibilities in any organization. Thus, the efficacy, speed, and suitability of judgments made by managers are crucial to the success of the firm. Decision-making is understood in the context of business intelligence as an organized process that depends on timely, accurate, and relevant information rather than just a choice between possibilities (Shollo, 2013).

There are several important aspects to decision-making. First, it is goal-oriented, since decisions are made in order to accomplish company objectives. Second, it involves choices, since managers choose from a range of options. Third, it is a continuous process, since managers make decisions regarding daily organizational activities. Additionally, decision-making is future-oriented since it influences future outcomes and

organizational success. Risk and uncertainty are common when making decisions, especially in fast-paced business environments where managers may not have all the information they require (David & et al., 2026). There are six components to the decision-making process. Decision-makers should use the following methodical approach while making non-programmed decisions, even though they can use mental shortcuts when making programmed judgments.

Figure 1: Decision-making process



Source: developed by the authors.

2.3 Business Intelligence and Decision-Making

Publications that highlighted the importance of business intelligence in facilitating better decision-making, enhancing financial performance, predicting market trends, and controlling risks. Adopting these tools is necessary to overcome obstacles including cost, technological complexity, and skills shortages in addition to gaining and maintaining a competitive advantage (Shao Valentinus Tsiu, 2024). Business intelligence is a potent tool for boosting market competitiveness through data-driven decision-making, according to a study on SMEs. According to the study, business intelligence enables SMEs to increase operational effectiveness, spot fresh growth prospects, and obtain in-depth knowledge of consumer preferences and rival plans. The use of predictive analytics, which enables SMEs to foresee market shifts and make proactive adjustments, is the main advantage of this. Although there are obstacles, such as a lack of resources and technical know-how, the report suggests ways to overcome them, like using cloud-based business intelligence tools and outsourcing services. Lastly, the ability of SMEs to compete with larger firms and achieve sustained growth depends critically on the efficient application of business intelligence (Blessing, 2024). Additionally, business intelligence models help SMEs to improve their competitive edge and make better decisions (Konstantina Ragazou, 2023).

Research consistently shows that business intelligence improves decision-making by increasing the quality and accessibility of information. Similarly, the evidence from the research done on Afghan SMEs shows that good accounting information improves managerial decision-making, especially when the managerial personnel have

sufficient financial literacy, thus proving the relevance of information quality to organizational decisions (Nael et al., 2026). These findings are further supported by evidence indicating that effective managerial practices lead to improved organizational outcomes and organizational profitability, highlighting the significance of informed managerial decision-making (Zaheer & Sadiq, 2025). Isik, Jones, and Sidorova found that technological business intelligence features, including data quality, user access, and system integration, are critical for business intelligence success regardless of the decision context. Improved business intelligence capabilities enable superior managerial judgment because managers can rely on cleaner data, faster access, and more integrated information when making decisions (Işık, 2013).

Recent empirical study further supports the notion that business intelligence directly and favorably influences the quality of strategic decisions. Abu-Alsondos (2023) found a positive and significant correlation between business intelligence management, business intelligence scope, data quality, and data visualization and the quality of strategic decision-making. Additionally, the scope of business intelligence and data visualization had particularly strong effects, suggesting that decision-making benefits from both having data and viewing it in a way that makes interpretation and action easier. This study shows that business intelligence influences specific aspects of decision quality rather than having a broad effect on decision-making. The study discovered that improved business intelligence administration was associated with higher decision quality, and that using effective visualization tools and guaranteeing high-quality data improves decision-making outcomes (Abu-AlSondos, 2023). Decision-making becomes even more important in the context of SMEs because business intelligence often faces resource constraints and uncertainty. The literature on SMEs claims that by helping companies recognize and seize new opportunities, business information supports decision-making. According to a recent analysis on business in SMEs, effective adoption of business intelligence gives SMEs more information to support decision-making and enhance organizational performance (Maleki, 2022).

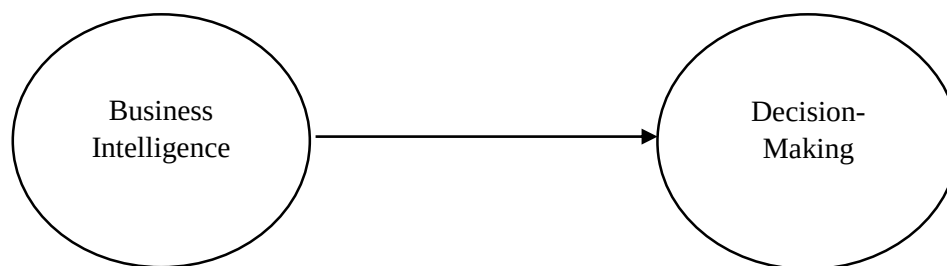
Data from MSMEs supports this notion even more. Business intelligence is crucial for quick decision-making and is used by owner-managers as a strategy to increase operational effectiveness and gain a competitive edge, according to Fabian's (2024) study in Nigerian micro, small, and medium-sized enterprises (Fabian, 2024). According to Akter Mahmuda, an organization's use of business intelligence (BI) tools can enhance strategic decision-making by providing real-time, accurate, and actionable insights. BI systems assist managers in understanding market trends, tracking the performance of high or potential competitors, and forecasting future opportunities and threats. Real-time reports and interactive dashboards make complex data more visually appealing, making it easier for decision-makers to make and visualize more informed and proactive decisions (Akter, 2025). A substantial amount of research looks at decision speed and comprehensiveness in addition to choice quality. Alzghoul (2024) asserts that business intelligence capabilities have an indirect effect on business

performance through decision-making speed and carefulness, showing that business intelligence enables firms to make decisions more rapidly while also carefully weighing their options. This is crucial since making the appropriate decision is only as important as making decisions in a timely and methodical manner (Alzghoul, 2024).

2.4 Theoretical Model

Although some studies investigated business intelligence effects on decision-making and found the positive and significant influence of BI on DM. The objective of this study is to test the direct impact of business intelligence on decision-making effectiveness through two dimensions: BIU and IQ of business intelligence in the context of Afghanistan Khost province.

Figure 2: Theoretical Model



Source: developed by the authors

3. RESEARCH METHODOLOGY

This study used an explanatory research design. And employs a quantitative method, using a structured questionnaire given to SMEs in Afghanistan's Khost province. Top-level managers, such as the board of directors, CEO, CFO, CTO, and COO, as well as middle-level managers, directors, supervisors, data analysts, and employees in charge of data retrieval and decision-making within the companies, made up the study's population. These individuals must be knowledgeable about the company's business processes and strategy in order to accurately respond to the questionnaire's questions. Business leaders who gather, assess, and use business intelligence (BI)-based data for decision-making were the target samples.

3.1 Source of Data

For this study, data were gathered from primary and secondary sources. Secondary data was gathered from books, scholarly journals, and published articles to give the study a theoretical and empirical basis. Additionally, a pretested structured questionnaire is used to gather primary data.

3.2 Method of data collection

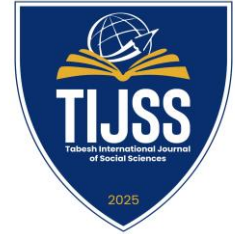
Primary data is gathered via survey from a variety of private and public SMEs, while secondary data is gathered from books, academic journals, and published articles. For survey respondents, the probability technique the simple random sampling method is used, Measuring the impact of business information on decision-making using a structured questionnaire with Likert-scale questions (1 = strongly disagree to 5 = strongly agree).

3.3 Scale of Measurements

The survey's questionnaire is designed to investigate business executives' perspectives on the usefulness and influence of business intelligence on decision-making. There are three sections to the questionnaire. The respondents' demographic data was recorded in the first part. The second section assessed BI usage and information quality, while the third section relates to decision-making. The scales for BIU were derived from the pretested questionnaire used by Xiaofeng Chen (2012) under the title "Impact of business intelligence and IT infrastructure flexibility on competitive advantage: an organizational agility perspective." The Cronbach's alpha values, which are 0.9 for BI usage indicators, show that all the measurement scales are highly reliable (Chen, 2012). The Cronbach's alpha coefficient for the IQ scales obtained from Azizah Ahmad's 2011 study, "Business Intelligence for Sustainable Competitive Advantage: The Case of Telecommunications Companies in Malaysia," showed that they were reliable and greater than 0.7 (Ahmad, 2011). The scales used in the study "Exploring strategic decision-making as a mediator between enterprise resource planning, innovation, strategic planning, and organizational performance" (Shaker M. Al Kahtani et al., 2024) served as the basis for the decision-making (DM) related scales. The study's measurement tools appear to be trustworthy based on the decision-making 0.884 Cronbach's alpha coefficient (Shaker M. Al Kahtani, 2024).

Table 1: Measurement items of Business Intelligence and Decision-Making.

Variables	Item Code	Questionnaire items	Scale
Business Intelligence	BIU1	Use of business intelligence to improve operational and performance efficiency.	1=Strongly Disagree to 5=Strongly Agree
	BIU2	Use of business intelligence to analyze and compare different data.	1=Strongly Disagree to 5=Strongly Agree
	BIU3	Use of business intelligence to generate actionable insights from data	1=Strongly Disagree to 5=Strongly Agree
	BIU4	Use of business intelligence to support decision-making.	1=Strongly Disagree to 5=Strongly Agree
	BIU5	Use of business intelligence to produce regular and standardized business performance reports.	1=Strongly Disagree to 5=Strongly Agree
	BIU6	Use of business intelligence to share insights within the organization.	1=Strongly Disagree to 5=Strongly Agree
Decision-Making	IQ1	Business intelligence provides accurate and reliable information	1=Strongly Disagree to 5=Strongly Agree
	IQ2	Our Organization analyzes relevant information during the Decision Making process	1=Strongly Disagree to 5=Strongly Agree
	IQ3	Our Organization employs quantitative analytical techniques for decision making	1=Strongly Disagree to 5=Strongly Agree
	IQ4	Our organization makes decisions quickly when needed.	1=Strongly Disagree to 5=Strongly Agree
	IQ5	Business intelligence help managers to make timely decisions.	1=Strongly Disagree to 5=Strongly Agree
	IQ6	Our organization managers regularly use BI report to make decisions.	1=Strongly Disagree to 5=Strongly Agree
	DM1	Decisions are based on accurate and reliable information.	1=Strongly Disagree to 5=Strongly Agree
	DM2	Analyzes relevant information during the Decision Making process.	1=Strongly Disagree to 5=Strongly Agree
	DM3		



DM4	Our Organization employs quantitative analytical techniques for decision making.	1=Strongly Disagree to 5=Strongly Agree
DM5	Our organization makes decisions quickly when needed.	1=Strongly Disagree to 5=Strongly Agree
DM6	Business intelligence help managers to make timely decisions Our organization managers regularly use BI report to make decisions	1=Strongly Disagree to 5=Strongly Agree

Source: developed by the authors

3.4. Sampling Technique

Random sampling was used in this study to minimize bias and guarantee that every worker in these two sectors has an equal chance of being chosen. In particular, the simple random method one of the four types of random methods is used by the researcher to ensure that each member of the population in the sample frame has an equal chance of being selected into the sample by using random numbers from a computer, random digit dialing, or some other random selection process (Burns, 2020).

Due to the endless population, opinions regarding the number and workforce of manufacturing and service SMEs in Khost province vary. The study employed a 95% confidence level ($Z = 1.96$), a 5% margin of error ($E = 0.05$), and a population proportion of $p = 0.5$, which is recommended when the population percentage is unknown. The study's sample size, which included managers and data analysts working at top-level, business-level positions, was determined using the infinite population formula. According to Cochran's sample size formula, the study's sample consisted of 384 respondents, as shown below:

$$n = \frac{z^2 * p * (1 - p)}{E^2} = \frac{1.96^2 * 0.5 * (1 - 0.5)}{0.05^2} = 384$$

Sample size =384

n= Sample size

Z= Z-score (confidence level)

P= Estimated Proportion of population (use 0.05 if unknown)

E= Margin of error

3.5 Data Analysis Techniques

The online questionnaire is distributed to the workers of companies in Khost province. After the data collection, for the analysis of the relationship BI and DM the study first employs descriptive analysis, using SPSS software. And for assessing the internal consistency, tested reliability, convergent validity and discriminant validity of the measures, the PLS-SEM technique is used in SmartPLSv.4.1.1.8 software, to test the relationship between business intelligence and decision-making through bootstrapping technique, in which subsample 5000, no sign change, confidence interval 95% and two-tailed test are selected to analyze data.

3.6 Measurement Model

This study used the following tests: collinearity test using the variance inflation factor (VIF); reliability test using Cronbach's Alpha, composite reliability (CR), convergent validity using the average variance extracted (AVE) and the Fornell-Larcker criterion; and discriminant validity using the Heterotrait-Monotrait (HTMT) correlations ratio.

4. RESULTS AND FINDINGS

4.1 Demographics profile

Table 2: Mean and standard deviation of variables

Variables	Mean	Std. Deviation	N
BIU	3.8724	0.78071	363
IQ	3.8563	0.77360	363
DM	4.0023	0.65335	363

Source: SPSS 25

The descriptive analysis indicates that, from all 363 valid responses, 352 or 97% of respondents were men and 11 or 3% of respondents were women. The largest percentage of people in the 20- to 29-year-old age range is 42.7%. The biggest percentage, 61.2%, held a Bachelor's Degree, followed by a doctorate (3%), a master's degree (15.2%), a high school (20.4%), and a researcher (0.3%). Given that the majority of these businesses are recent entrepreneurs in the area, the maximum proportion of years of experience, 38%, is between the range of 1<5 years. Lastly, the largest share of job positions, 147 or (40.4%) are held by respondents who manage firms and make top managers. 119 or 32.8% of middle managers and 97 or 26.7% of employees participated in the survey. Accordingly, 174 respondents were from medium-sized businesses and 189 were from small businesses. The majority of participants were from manufacturing companies, 197 or 54.3%, and from services companies involved, 166 or 45.7%. The mean and standard deviation of variables are revealed in the table below.

4.2 Collinearity

Table 3: VIF values

Items	Outer VIF		Inner VIF
BIU1	2.505	BIU -> DM	1.364
BIU2	3.367	IQ -> DM	1.364
BIU3	1.482		
BIU4	2.723		
BIU5	2.307		
BIU6	2.177		
DM1	2.222		
DM2	2.449		
DM3	1.741		
DM4	2.315		
DM5	1.682		
DM6	2.598		
IQ1	2.965		
IQ2	2.048		
IQ3	3.596		
IQ4	3.519		
IQ5	2.419		
IQ6	1.658		

Source: SmartPLSv.4.1.1.8

The variance inflation factor (VIF) is a commonly used indicator of collinearity; generally speaking, if the VIF coefficient is more than 5.0, there may be serious multicollinearity, and between 3 and 5 is acceptable; VIF values below 3 indicate no collinearity. Multicollinearity prevents the researcher from determining the relative importance of one independent variable in relation to another, expands standard errors, and renders significance tests of independent variables inaccurate (Hair & Alamer, 2022). The two types of VIF are called outer and inner VIF. The outer VIF shows the degree of collinearity between the latent variables and their indicators, while the inner VIF shows the degree of collinearity between the constructs (latent variables) that make up the model (Alshibly, 2020).

The above table 3, demonstrates that the VIF value is below from specified criterion 5.0. Thus there is no multicollinearity and collinearity problem in the measurement model.

4.3 Reliability and Validity

Reliability is the extent to which a measurement tool consistently produces the same results when employed under similar conditions; Cronbach's alpha is used to assess the internal consistency of scale items. (Mohammad Ismail & Shafiq, 2026). Reliability is a major concern when using a psychological test to evaluate a trait or behavior (Drost, 2011). Sra Sitan Al Qasrawi (2022) cited that Cronbach's α value of greater than 0.70 is accepted. Furthermore, a research instrument's validity is determined by how well it evaluates the concept it is meant to assess. It is essential for ensuring the accuracy and significance of a study's findings; high validity boosts the results' credibility and practical utility by enabling researchers to make informed decisions and wise interpretations based on the data. AVE value must be greater than 0.5 and the composite reliability must be 0.6 or higher to ensure convergent validity (Mohammad Ismail & Shafiq, 2026).

Table 4: Reliability Coefficients/Cronbach's Alpha and Composite reliability

Variables	Measured Cronbach's Alpha (CA)	Composite reliability (CR)	Average variance extracted (AVE)	Approval
BIU	0.894	0.899	0.657	Approved
DM	0.868	0.875	0.605	Approved
IQ	0.871	0.878	0.611	Approved

Source: SmartPLSv.4.1.1.8

The table 4, demonstrated that the questionnaire's overall Cronbach's alpha coefficient, which evaluates internal consistency among its items, accepted. The questionnaire BIU, DM and IQ indicators are exceptionally reliable, with a Cronbach's α value of greater than 0.70 (sra Sitan Al Qasrawi, 2022).

Every construct in this study has a composite reliability value higher than the cutoff, and the study's measurement tools appear to be reliable based on the Cronbach's and composite reliability values of the constructs. Composite reliability is an alternative score that is believed to be a more accurate measure of reliability than the Cronbach's Alpha. It was developed to untie the assumptions used to calculate Cronbach's Alpha (Chen, 2012).

4.4 Convergent validity

The average variance extracted (AVE) must be greater than 0.5 and the composite reliability must be 0.6 or higher to ensure convergent validity (Mohammad Ismail & Shafiq, 2026)

Table 5: CR and AVE values and R^2 values for DM

No	Variables	Composite reliability (CR)	Average variance extracted (AVE)	R^2
1	BIU	0.899	0.657	0.752
2	DM	0.875	0.605	
3	IQ	0.878	0.611	

Source: SmartPLSv.4.1.1.8

This table demonstrates that the AVE value appears to be greater than the criteria 0.5, and the composite reliability is higher than the suggested threshold 0.7, indicating the internal consistency.

Table 6: Outer Loading Matrix

	BIU	DM	IQ
BIU1	0.838	-	-
BIU2	0.857	-	-
BIU3	0.691	-	-
BIU4	0.820	-	-
BIU5	0.837	-	-
BIU6	0.808	-	-
DM1	-	0.802	-
DM2	-	0.836	-
DM3	-	0.657	-
DM4	-	0.782	-
DM5	-	0.737	-
DM6	-	0.838	-
IQ1	-	-	0.765
IQ2	-	-	0.715
IQ3	-	-	0.876
IQ4	-	-	0.814
IQ5	-	-	0.798
IQ6	-	-	0.709

Source: SmartPLSv.4.1.1.8

The convergent validity of indicators like those mentioned by Alshibly (2020) is displayed in the above table, taking into account the indicators' outer loading, which is significant at the level of 5% and exceeds (Alshibly, 2020).

4.5 Discriminant Validity

The Fornell & Larker criterion and the HTMT ratio (Heterotrait-Monotrait Ratio), suggested by Jörg Henseler et al. (2014), are used to evaluate discriminant validity. According to Fornell & Larker, the condition is satisfied if the square root of the AVE value is higher than the correlations with other constructs. (Sarstedt, 2014).

Table 7: Criterion of Fornell & Larker

No	Constructs	BIU	DM	IQ
1	BIU	0.810		
2	DM	0.635	0.778	
3	IQ	0.516	0.834	0.782

Source: SmartPLSv.4.1.1.8

The table 7, shows that the square roots of AVE are bigger than the correlations of constructs that have with others constructs.

4.6 Heterotrait-Monotrait Ratio (HTMT)

The degree of the difference between overlapping constructs was measured using this test, which was used to double-check the discriminant validity. A value between zero and one is acceptable, and less than one indicates strong reliability (Muawia Ramadan, 2020). Some authors recommend HTMT criteria of 0.85, while others suggest 0.90. To ensure discriminant validity, the HTMT value of constructs should be less than the specified criterion (Sarstedt, 2014).

Table 8 : Heterotrait-monotrait ratio (HTMT) – Matrix

No		HTMT ratio values
1	DM <-> BIU	0.705
2	IQ <-> BIU	0.578
3	IQ <-> DM	0.950

Source: SmartPLSv.4.1.1.8

Table 8, demonstrates the constructs' validity because the values of the constructs (DM <-> BIU & IQ <-> BIU) are below the recommended requirement, but the constructs (IQ <-> DM) are acceptable, because Muawia Ramadan (2020) detailed a value between zero and one is acceptable. As a result, discriminant validity is verified.

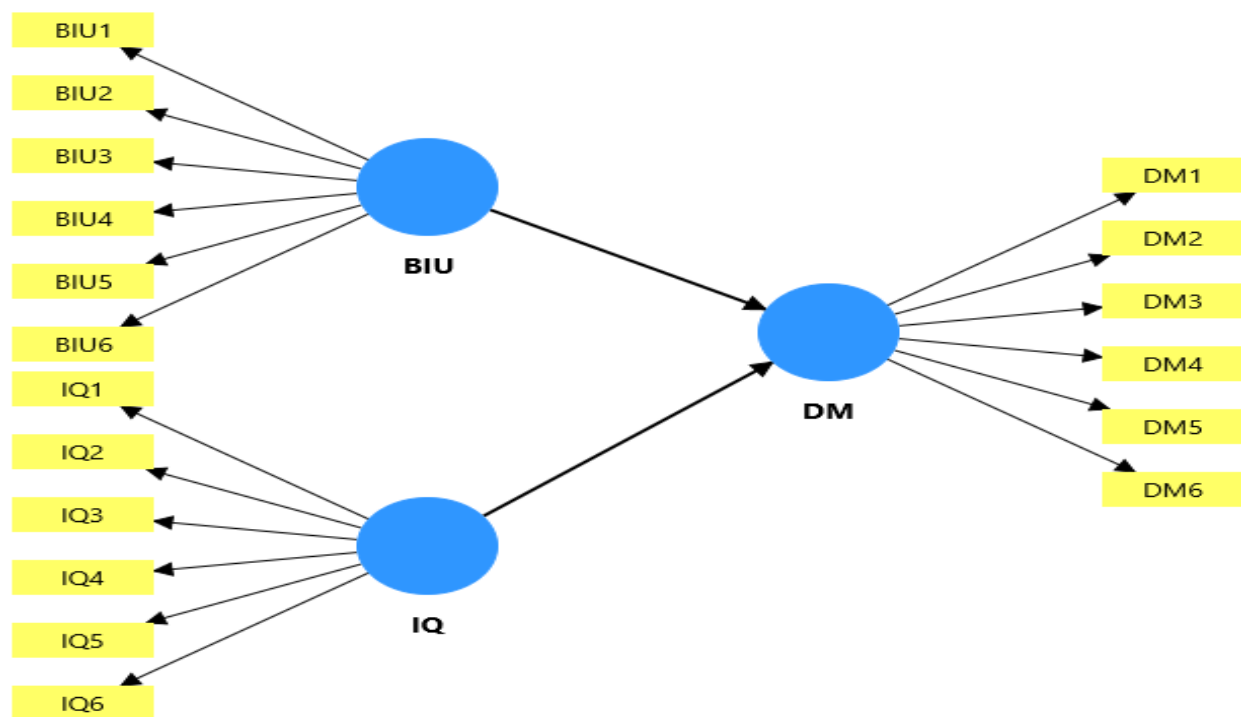
4.7 Structural Model

After the measurement model has been shown to be valid and reliable, it is important to confirm the path coefficient values and statistical significance of relationships between the variables in the structural model in order to assess the proposed hypothesis. This is done by evaluating the standardized path coefficient (β -value)

with a value equal to or above 0.1 and the related t-values with values above 1.96 or below -1.96 at 0.05 at the level of significance, i.e. $P\text{-Value} < 0.005$ (Muawia Ramadan, 2020).

4.8 Measurement Model Results

Figure 3: Measurement Model Results



Source: SmartPLSv.4.1.1.8

Table 9: Path coefficient and T-values

	β -value	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
BIU -> DM	0.278	0.277	0.035	7.966	0.000
IQ -> DM	0.691	0.689	0.033	21.026	0.000

Source: SmartPLSv.4.1.1.8

Business intelligence usage, with results ($\beta=0.278$, $t=7.966$), shows a positive and significant impact on DM, and information quality, with results ($\beta=0.691$, $t=21.026$), has a direct strong and significant positive impact on decision-making, according to all extracted values by bootstrapping, β -value, and T-values of direct effects.

The decision-making dependent variable is explained by the business intelligence independent variable components BIU and IQ 75.2% when the coefficient of determination (R^2) for DM is 0.752, as shown in Table

5. R2 is a statistical value that explains the amounts of dependent variable variance that are explained by the independent variable; an acceptable value of R2 is between zero and one (Muawia Ramadan, 2020).

Table 10: f-Square assessment

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
BIU -> DM	0.229	0.231	0.062	3.698	0.000
IQ -> DM	1.413	1.422	0.263	5.371	0.000

Source: SmartPLSv.4.1.1.8

The examination of f^2 values indicate to assess the contribution of exogenous constructs to endogenous constructs in the structural model. According to Cohen's (1988) guidelines, as cited (Sara Kazemi, 2025), an f^2 value of 0.02 indicates a small effect size, 0.15 indicates a medium effect size, and 0.35 indicates a large effect size. The result of the effect size is below.

The relationship between the use of business intelligence and decision-making shows a f-square value of 0.229, indicating a medium effect size, and the result is statistically significant and the ($T=3.698$, $p=0.000$), indicating that the use of business intelligence has a meaningful contribution to explain the variance in decision-making.

Similarly, the relationship between the quality of information and decision-making demonstrates an f square value of 1.413, shows a very large effect size, the result is highly significant ($T=5.371$, $p=0.000$), suggesting that information quality is the strongest predictor of decision-making.

In overall, the f^2 results reveal that exogenous variables have significant effect on endogenous variable.

Table 11: Hypotheses testing

Hypotheses	Constructs	T statistics (O/STDEV)	P values	Status
H ₁	BIU -> DM	7.966	0.000	Accepted
H ₂	IQ -> DM	21.026	0.000	Accepted

Source: SmartPLSv.4.1.1.8

Hypothesis testing results in the above table indicate that H1 is accepted because the relationship between BIU and DM is significant ($t=7.966$, $p=0.000$), meeting the suggested criterion that T-values must be above 1.96 or below -1.96. Additionally, the results showed that IQ and DM have a positive and significant relationship ($t=21.026$, $p=0.000$), indicating that the significance of the hypothesis was expressed higher than the suggested criterion, above 1.96 or below -1.96.

4.9 DISCUSSION

The purpose of this study was to assess how the use of business intelligence affected the efficacy of decision-making among Afghan SMEs using data from the province of Khost. The results of this study proved that business intelligence (BI) has a significant and beneficial impact on decision-making (DM). In particular, the two dimensions of business intelligence (BIU) and IQ showed significant and favorable correlations with decision-making effectiveness.

Decision-making is positively and significantly impacted by BI usage, according to the substantial path coefficient of BIU ($\beta=0.278$, $p=0.000$). The outcome shows that using business intelligence tools can increase the efficacy of decision-making. SMEs may increase their agility and efficiency by using business intelligence to turn raw data into meaningful insights. This result is in line with earlier research that demonstrated business intelligence systems improve organizational competitiveness, decision-making, and company performance (Konstantina Ragazou, 2023; Sümeyye Öztürk, 2021; Eidizadeh Rosa, 2017; Chen, 2012).

Additionally, the study's path coefficient ($\beta=0.691$, $p=0.000$) indicated that IQ had a greater beneficial influence on decision-making. This finding implies that fast, accurate, trustworthy, and pertinent information is essential to enhancing SMEs' capacity to successfully compete. Additionally, the high-quality data enables managers to anticipate industry trends, spot opportunities, and respond promptly (Arisa, 2013). Additionally, the results corroborate RBV theory, which contends that valuable, uncommon, unique, and non-replaceable resources give businesses a lasting competitive edge (Barney, 1991). Information quality and BI skills can be regarded in this study as strategic resources that improve the efficacy of decision-making. SMEs who invest in BI technology and efficient information management systems are better positioned to obtain a competitive advantage, according to the report.

SMEs in Afghanistan encountered a number of obstacles when putting BI systems into place, such as inadequate technological infrastructure, a lack of skilled labor, erratic electricity, financial constraints, and a lack of knowledge about digital technologies. These obstacles prevented SMEs from fully utilizing BI capabilities. The use of the aforementioned system enhances decision-making quality, contributes to innovation, operational efficiency, customer happiness, and long-term business stability. This study emphasizes the significance of BI for SMEs in developing economies like Afghanistan.

5. CONCLUSION

The effects of business intelligence on decision-making in the context of small and medium-sized enterprises (SMEs) operating in Afghanistan, Khost province, were investigated in this research paper using a quantitative method, a deductive approach. The data was gathered by conducting a survey using a structured questionnaire from 379 respondents who work with SMEs as top, middle-level managers and employees who are responsible

for data retrieval and analysis; 16 respondents' responses showed that 4.22% of all responses were invalid and were removed from the analysis, while 363 respondents' responses were valid and included in the data analysis.

After the cleaning, the collected data were analyzed by SmartPLSv.4.1.1.8 software using the PLS-SEM technique, a contemporary SEM model. The data analysis reveals that there is a positive and significant relationship between the variables BIU and DM as well as between the variables IQ and DM at SMEs in Khost province.

Business intelligence can have an impact on decision-making, as shown by the results of the BIU, path coefficient ($\beta=0.278$, $p=0.000$), and IQ path coefficient ($\beta=0.691$, $p=0.000$). According to the findings, BI systems are crucial for improving decision-making quality, fostering innovation, increasing operational effectiveness, facilitating information exchange, fostering agility, and more.

By showcasing the beneficial and noteworthy impacts of business intelligence on decision-making at SMEs in Khost, Afghanistan, this study successfully met all of its goals. Additionally, business intelligence capabilities serve as a useful tool that helps SMEs to gain a competitive edge, validating the RBV theory.

Overall, this study highlights that BI systems are crucial strategic processes and systems for SMEs to boost performance, foster innovation, improve the caliber of decision-making, and guarantee long-term sustainability and competitiveness.

The coefficient of determination ($R^2=0.752$) shows that both BI variables accounted for 75.2% of the variance in decision-making, despite the study's noteworthy findings. However, the extra variables may play a major role in explaining decision-making among SMEs.

Examination of f^2 values indicate to assess the contribution of exogenous constructs to endogenous constructs in the structural model, the relationship between the use of business intelligence and decision-making shows f -square value 0.229, indicating a medium effect size, and similarly, relationship between the quality of information and decision-making demonstrates f^2 value 1.413, shows a very large effect size, suggesting that information quality is the strongest predictor of decision-making.

5.1 Recommendation

SMEs should invest in modern BI technologies and software to support decision-making processes. Promote data-driven decision-making based on accurate and timely information. Use BI dashboards and reporting systems to monitor performance, improve efficiency, and enhance competitiveness. And support IT professionals and employees to ensure the successful implementation of business intelligence systems. Although this study offers insightful information about how BI affects DM among Afghan SMEs, it has certain

recommendations that should be noted and taken into consideration for future research. For instance, because the study is geographically restricted to SMEs in Khost province, its conclusions might not apply to all SMEs in Afghanistan due to regional variations in organizational performance, technology infrastructure, and environmental conditions. Additionally, the study only looked at two aspects of BI—the use of BI and information quality in decision-making. However, other elements that were not covered in the study, such as market orientation, organizational culture, leadership style, and innovation capabilities, might have an impact on the decision-making effectiveness.

5.2 Limitation of the study

Manufacturing and services SMEs are chosen only in this study, and also the information is gained from just a questionnaire. The study is geographically limited to Small and Medium-Sized Enterprises (SMEs) in Khost province, so the findings may not represent all the Small and Medium-Sized Enterprises (SMEs) across Afghanistan. And this study focused on only two dimensions of business intelligence, namely BI usage and information quality in influencing decision-making effectiveness.

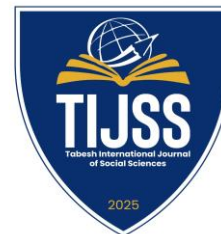
5.3 Conflict of interest

The authors declare that they have no conflict of interest.

6. REFERENCES

- Abdallah, S., Altahoo, M., & Almannaei, M. M. (2024). The Impact of Business Intelligence on Decision-Making Process and Customer Service. ResearchGate.https://www.researchgate.net/publication/379100361_The_Impact_of_Business_Intelligence_on_Decision-Making_Process_and_Customer_Service.
- Abu-AlSondos, I. A. (2023). The impact of business intelligence system (BIS) on quality of strategic decision-making. *International Journal of Data and Network Science*, 7(4), 1901–1912, <https://doi.org/10.5267/j.ijdns.2023.7.003>.
- Ahmad, A. (2011). *Business Intelligence for Sustainable Competitive Advantage: The Case of Telecommunications Companies in Malaysia*. Curtin Graduate School of Business.
- Akter, M. (2025). *Enhancing SME Competitiveness: The Role of Business Intelligence in Data-Driven Decision-Making*. Oulu University of Applied Sciences, Bachelor's Thesis.

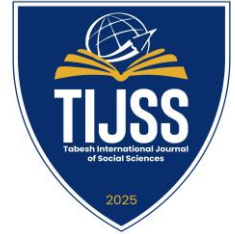
-
- Al-Hattami, H. M., Ahmed, A. A., Hashed, A. A., Jawahar, D. K., Alsoufi, M. A. Z., Gaber, M. M. A., & Shuraim, A. M. A. (2022). Impact of AIS success on decision-making effectiveness among SMEs in less developed countries. *Information Technology for Development*, 30(3), 1–21. <https://doi.org/10.1080/02681102.2022.2073325>
- Alshibly, H. H. (2020). Investigating the Effectiveness of Business Intelligence Systems: A PLS-SEM Approach. *International Journal of Management Sciences and Business Research* Vol-9, Issue 9, 33-49.
- Alzghoul, A. K. (2024). How business intelligence capability impacts decision-making speed, comprehensiveness, and firm performance. *Information Development*, 40(2), 220-233, <https://doi.org/10.1177/02666669221108438>.
- Arisa, S. (2013). The role of business intelligence in organizational decision-making. Copenhagen: Copenhagen Business School, 978-87-92977-33-5 (316).
- Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of management* Vol.17, No.1, 99-120.
- Bhatiasevi, V., & Naglis, M. (2020). Elucidating the determinants of business intelligence adoption and organizational performance. *Information Development*, 36(1), 78–96. <https://doi.org/10.1177/0266666918811394>
- Blessing, M. (2024). The Business Intelligence Roles in Enhancing SME Growth and Market Competitiveness. Wayzman Kolawole, 1-6.
- Bright, D. S., & Cortes, A. H. (2019). *Principles of management*. OpenStax, Rice University.
- Carlos Andrés Tavera Romero, J. H. (2021). Business Intelligence: Business Evolution after Industry 4.0. *Sustainability* 2021, 13(18), 10026; <https://doi.org/10.3390/su131810026>, 1-12.
- Chen, X. (2012). IMPACT OF BUSINESS INTELLIGENCE AND IT INFRASTRUCTURE FLEXIBILITY ON COMPETITIVE ADVANTAGE: AN ORGANIZATIONAL AGILITY PERSPECTIVE. *Dissertations, Theses, and Student Research from the College of Business*. 32 <https://digitalcommons.unl.edu/businessdiss/32>, 32.



-
- Drost, E. (2011). Validity and Reliability in Social Science Research. *International Perspectives on Higher Education Research* 38(1), 105-124.
- Fabian, A. A. (2024). Business Intelligence and Decision-Making in Micro Small and Medium Enterprises in Africa. *Scholars Journal of Economics, Business and Management* 11(04), 124–133.
- Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, elsevier journal, 1-16, <https://doi.org/10.1016/j.rmal.2022.100027>.
- Işık, Ö. J. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management*, 50(1), 13–23.
- Kamali, A. M. (2009). The Role of Business Intelligence (BI) in Enhancing the Competitive Advantages of Organization. ARABIAN GULF UNIVERSITY, Thesis, Case Study: Batelco Company.
- Konstantina Ragazou, Z. (2023). Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage. *Discover Analytics*, springer, <https://doi.org/10.1007/s44257-022-00002-3>, 1-15.
- Lahbi, H. (2018). The Power of Business Intelligence on the Decision-Making Process at Linköping University. Master's thesis in Business Administration Strategy and Management in International, SRN number: LIU-IEI-FIL-A--18/02856—SE.
- Larcker, C. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research* Vol. 18, No. 1, 39-50, <https://doi.org/10.2307/3151312>.
- M.Olszak, C. (2014). Towards an Understanding Business Intelligence. A Dynamic Capability-Based Framework for Business Intelligence. 2014 Federated Conference on Computer Science and Information Systems, 1103-1110, https://annals-csis.org/Volume_2/drp/68.html.
- Maleki, R. & (2022). Business Intelligence Analysis in Small and Medium Enterprises. *International Journal of Innovation in Marketing Elements*, 2(1), 1–11, <https://doi.org/10.59615/ijime.2.1.1>.

-
- Mohammad Ismail, S., & Shafiq, H. (2026). Analyzing the Impact of Ethical Sales Behavior on Customer Satisfaction: A Study of Afghanistan's Passengers Transport Industry. *Journal of Social Sciences & Humanities*, 128-153, <https://doi.org/10.62810/jssh.v3i1.111>.
- Muawia Ramadan, H. S. (2020). Sustainable Competitive Advantage Driven by Big Data Analytics and Innovation. *Applied Sciences*. 10, 6784;, 1-14, doi:10.3390/app10196784.
- Nael, A., Zaheer, A., Ghafourzay, H., Ahmadi, Z., & GHAFOURZAY, H. (2026). The Role of Accounting Information in Improving Decision-Making for Small and Medium-Sized Businesses in Kabul, Afghanistan: Evidence on the Moderating Effect of Financial Literacy. *Cureus Journals*, 3(1). <https://doi.org/10.7759/s44404-026-00070-8>
- Parkin. (1996). *Management Decisions for Engineers*. <https://books.google.com.af/books?id=-JbU42BSSrsC> : Emerald Publishing Limited.
- Ragazou, K., Passas, I., Garefalakis, A., & Zopounidis, C. (2023). Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage. *Discover Analytics*, 1(1), Article 2. <https://doi.org/10.1007/s44257-022-00002-3>
- Ramesh Sharda, D. D. (2018). *BUSINESS INTELLIGENCE, ANALYTICS, AND DATA SCIENCE: A Managerial Perspective*. United Kingdom: Pearson Education, ISBN 978-0-13-463328-2.
- Sael, Q. D. (2017). Next Generation Business Intelligence and Analytics: A Survey. *IEEE COMMUNICATIONS SURVEYS & TUTORIALS*, 1-11.
- Sara Kazemi, M. G. (2025). Presenteeism, moral courage, and moral disengagement among nurses: a crosssectional structural equation modeling study. *BMC Nursing*, 1-10.
- Sarstedt, J. H. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Springerlink.com*, 115-135, DOI 10.1007/s11747-014-0403-8.
- Shaker M. Al Kahtani, N. A. (2024). Exploring strategic decision making as a mediator between enterprise resource planning, innovation, strategic planning, and organizational performance. *Discover Sustainability*, <https://doi.org/10.1007/s43621-024-00532-8>.

-
- Shao Valentinus Tsiu, M. N.-M. (2024). Applications and Competitive Advantages of Data Mining and Business Intelligence in SMEs Performance: A Systematic Review. ResearchGate.https://www.researchgate.net/publication/383988669_Applications_and_Competitive_Advantages_of_Data_Mining_and_Business_Intelligence_in_SMEs_Performance_A_Systematic_Review.
- Shollo, A. (2013). The role of business intelligence in organizational decision-making. Business school, <https://doi.org/10.1111/isj.12071>.
- sra Sitan Al Qasrawi, K. K. (2022). The Impact of Business Intelligence on Strategic Entrepreneurship: The Mediating Role of Organizational Agility. International Review of Management and Marketing, 12-20, DOI: <https://doi.org/10.32479/irmm.13336>.
- Sümeyye Öztürk, A. Ü. (2021). Effect of Business Intelligence on Competitive Advantage Case of Ankara IT Sector. Journal of Information & Knowledge Management, Vol. 21, No. 1 (2022) 2250007 (28 pages),,c World Scientific Publishing Co.,DOI: 10.1142/S0219649222500071, 1-28.
- Teresa Guarda, M. S. (2013). Business Intelligence as a Competitive Advantage for SMEs. International Journal of Trade, Economics and Finance, Vol. 4, No. 4, August 2013 DOI: 10.7763/IJTEF.2013.V4.283, 187-190.
- Tirno, R. R. (2024). Effect of bu siness intelligence on organizational competitiveness- exploring the mediation of technology anxiety. ScienceDirect, Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/bync-nd/4.0/>).<https://doi.org/10.1016/j.chbr.2024.100536>, 1-11.
- Titik Kusmantini1, T. M. (2021). Analysis of the Effect of Business Intelligence on Competitive Advantage through Knowledge Sharing and Organizational Innovation in Export Companies. The Asian Institute of Research, Journal of Economics and Business, Vol.4, No.1, 2021: 245-254, ISSN 2615-3726,, 245-254, DOI: 10.31014/aior.1992.04.01.335.
- United Nations Development Programme. (2026). Private sector mapping in Afghanistan. UNDP.
- Venkatakrishnan, R. (2020). DESIGN, IMPLEMENTATION, AND ASSESSMENT OF INNOVATIVE DATA WAREHOUSING; EXTRACT, TRANSFORMATION, AND LOAD(ETL); AND ONLINE



ANALYTICAL PROCESSING(OLAP) IN BI. International Journal of Database Management Systems (IJDMS) Vol.12, No.3, , 1-6,DOI : 10.5121/ijdms.2020.12301 .

Vincent English, M. H. (2018). Business Intelligence as a Source of Competitive Advantage in SMEs: A Systematic Review. DBS Business Review 2,LicenseCC BY-NC-SA 4.0,DOI:10.22375/dbr.v2i0.23, 10-32.

World Bank. (2024). Afghanistan private sector rapid survey: Round 3. World Bank Group.

Zaheer, A., & Sadiq, A. (2024). The Impact of IT Integration in Human Resource Management on Employee Productivity: A Study of Afghanistan's NGOs. Salam Academic Journal, 9(16), 7-24.
<https://doi.org/10.64104/v9.SecondRound.Issue.6.n6.2024>

Zaheer, A., & Sadiq, A. (2025). The Influence of Traditional Management Practices on Employee Satisfaction, Turnover Intention, and Perceived Organizational Profitability. Khurasan University Business Administration Journal, 2(1).