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Business Intelligence, technology anxiety and Strategic Learning as Drivers of Strategic Decision-Making: The Mediating Role of Decision-Making Agility

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ABSTRACT

This study examines the relationships between business intelligence (BI), strategic learning (SL), technology anxiety (TA), decision-making agility (DMA), and strategic decision-making (DM) in the Iraq's IT sector. A quantitative research design has been considered and employed, and survey data were collected from 224 top officials from the targeted sector. The analysis was conducted using Smart PLS 4.0 to test both direct and mediating effects. However, the study also focuses on testing the measurement model before applying the structural equation modelling technique. The results show that DMA has a positive impact on strategic DM, and BI significantly enhances DMA but not DM on direct grounds. Moreover, it is observed that strategic learning tends to exert a positive influence on both DMA and DM, while TA shows no significant effect on the given constructs. Mediation analysis also additionally claiming that DMA plays a significant mediating role between SL and DM, and between BI and DM, respectively. These findings highlight the importance and organizational need of agility as a key mechanism through which learning and intelligence improve strategic decision-making in technology-driven organizations specifically in the Iraq region and in generally for the other regional economies. Besides, the limitations and future directions are also discussed.

1. Introduction

The utilisation of interactive systems has progressed rapidly during the era of digital transformation, responding to the evolving requirements of users [1]. These systems can generally be categorised into two main types, particularly multimodal interaction platforms that incorporate diverse input and output modalities such as voice, touch, gesture, and visual interfaces. This categorisation is due to their adaptability and user-centred orientation [32]. These platforms are designed to emulate natural human communication patterns while also enhancing system usability [30]. As the user base becomes increasingly diverse, expectations for how such systems should

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function, appear, and respond continue to grow. Among the influencing factors, aesthetic preference stands out as both a critical and underexplored aspect. This qualitative dimension significantly impacts user engagement, decision-making, and overall satisfaction with interactive systems [21]. Integrating these factors into system models has the potential to elevate the quality of user interaction and the effectiveness of decision-making processes facilitated by these systems.

In the world market, strategic decision making has become a very important factor for the success of any business, especially in the economies like Iraq. Business intelligence (BI), strategic learning (SL), technology anxiety (TA), decision-making agility (DMA), and strategic decision-making (DM) in the Iraq IT sector. This is an enabling of access to visualization tools and analytics about market trends, consumer behaviors, and operational efficiency through the adoption of BI in reporting towards real time by information technology companies in Iraq. With rapid technological change redefining the context in Iraq economy, understanding the influence of BI along with other factors towards strategic decision making will support the pursuit of innovation and rationalization towards more sustained growth performance. Hmoud et al. [11] state that business intelligence is a term that describes the set of software capabilities companies can use to access, analyze, and develop actionable insights for data-driven decision making. Advanced BI systems are adopted by MOST companies for enabling them to retrieve, analyze and make sense of big data that provides the top management with valuable insights related to the market trend, consumer behavior, and operational efficiency. Majali et al. [15] stressed that BI technologies have not only streamlined internal operations but also enabled more proactive behavior by Jordanian business leaders. It integrates data mining along with data storage methodologies and a bunch of tools that help to derive more information based on data. It is the processing and thereafter using data for decision-making. According to Hmoud et al. [11] Artificial Intelligence is defined as the science and engineering of making intelligent machines especially intelligent computer programs. It is an academic field of study; robots are also a product of AI research. It includes many advanced algorithms in computer science through which complicated things can be done in both robots and games. Hmoud et al. [11] note that “BI is the issue of utmost relevance in making available and unifying data that drives decision making. According to Niu et al. [18], mangers and other similar individuals in the organizations of today are still at sea regarding the application of business intelligence in strategic decision-making. Strategic decision-making is described as a slow and shared process, which is influenced by various inputs that are specific to the history, current situation, and future foresight”. Decision-making is the process that is developed in a systematic way to select between given alternatives. It can be effectively defined as the act of recognizing an issue, accumulating all the needed data, and assessing different courses of action. When a decision is made in this manner outlined step-by-step, it will be easy to comprehend, with respect to the action that will be undertaken because it clearly shows the information needed and the various alternatives [23].

Strategic learning is the process through which a firm picks up new knowledge that then pushes a change in its strategy [4]. Of course, it is widely believed that change itself is not built into learning. Sometimes a firm carries out a strategy and gains knowledge that supports staying on the same path over a period, hence not changing it all. Still, maybe because it is hard in practice to tell when a firm has really grown its strategy related knowledge, literature often treats visible strategic change as proof that strategic learning happened. In line with this idea, the authors like Voronov and Yorks [29] describe strategic learning as a process of continuously crafting and reformulating strategies. In a similar way, Ambrosini and Bowman [2] are claiming that strategic learning connects directly to the core management question of how organizations change their strategy to build and keep competitive advantage. On the other hand, as new technologies grow, it has become very important to look at both the ability and the willingness of customers to use them. Therefore, the central idea about the

usage of the technology readiness was created in order to explain how consumers use new technologies to get things done [19]. Meanwhile, the technology readiness is seen as a general tendency to accept technology, and it should shape a person's inclination to try new technologies [19]. A related idea is computer or technology anxiety Igbaria and Parasuraman [12], which describe as the fear, worry, and even hope people feel when they think about using or actually use computer technology [24].This anxiety can show up as being overly timid with computers, therefore, making some sort of negative remarks about computers and information science, while trying to cut down the time spent on computers. Moreover, there have been several studies suggest computer anxiety is common. One study said about 55 percent of Americans feel some level of technophobia. Others argue that millions of American workers and about one third of college students [7] struggle with anxiety related to computers. Only a small portion have very severe anxiety (Rosen and Maguire, 1990), but it is still clear that computer anxiety matters. Some researchers even see it as a reason why more computer use in society may not always be effective. The central research issue addressed within this study pertains to the capacity of Business Intelligence (BI) along with the technology anxiety, and strategic learning to facilitate strategic decision-making processes in information technology firms as located in the region of Malysia. A primary data analysis is employed to elucidate the specific challenges and opportunities that Iraq companies encounter in making some strategic decisions.

2. Literature Review

Business intelligence has been at the forefront of unifying the decision-making process in various companies, chiefly within the marketing departments. Naderi [17] say that BI has garnered considerable popularity among top-level executives from various industries due to its ability to facilitate well-informed decision-making. It provides an idea about the effect of business intelligence on decision-making improvement. As stated by Hmoud et al. [11], the current trend in the business environment resulting from globalization, market competition, and the information technology revolution has radically changed, Adoption of BI by many organizations around the world has become an integral driver in the cycle of decision-making toward gaining economic development. The reviewed studies provide valuable insights into the thematic scope of the current research. They primarily emphasize the role of Business Intelligence (BI) in enhancing operational performance within various Iraqi marketing firms seeking to improve their strategic standing [13]. Their study examined the impact of BI components which are entitled as data warehousing, data mining, and report generation on the effectiveness of decision-making within the Islamic International Arab Bank. The dimensions of decision-making assessed included the timeliness of decisions, the ease of implementation, and the degree of employee acceptance. A quantitative descriptive approach was employed, utilizing a structured questionnaire consisting of 28 items. The survey targeted senior management, with 50 executives participating; all returned questionnaires were deemed valid for analysis. The results showed a clear and strong link between business intelligence and better decisions in the bank. In simple terms, when the bank uses BI well, leaders make smarter, faster choices across different areas. Based on this, we suggest putting more attention into BI as a core part of how the bank works and competes. That means investing in better tools and systems, keeping the data tidy and up to date, and making sure people know how to use the tools in their daily work. Decision making should also be improved by moving quickly from plans to action, keeping steps easy to follow, and getting staff on board early. Involve employees through open meetings, brainstorming, and regular two-way conversations. This kind of participation builds trust, improves the quality of ideas, and helps everyone pull in the same direction.

This study by Majali et al. [15], explored the association that links business intelligence

capabilities with decision quality in Jordanian telecommunications firms. The research set its focus on identifying which factors of BI yield decision quality specifically in the given context. To carry out this objective, a questionnaire was developed, and the opinions of middle- and top-level managers of various business departments were elicited with the help of BI tools being used in decision-making processes. For a sample of 103 respondents, the study has applied the SEM strategy for the purpose of statistical estimation. The results show that there is a significant impact of selected exogenous constructs on the decision-making quality. Specifically, the factor of system quality has been recognized the strongest driver of better decisions. On the other hand, information quality and service quality also matter a lot. These findings are useful for telecom firms because they underline how important BI systems are for improving decision making.

Apart from the above explained factors affecting strategic decision making, the term technology anxiety has also gained some of a valuable attention from the researchers. However, some mixed findings have been found. For example, Mokyr et al. [16] have their view that people consider the technology as the tool towards the growth of the economy. However, this factor of technology has also carried some worries for people too. These anxieties show up in a few ways. Firstly, there is a fear in the mindset of the people that new technology replaces workers with machines with an ultimate rise in unemployment too. Secondly, people also worry about the moral side of all this for human welfare. Back in the Industrial Revolution the fear was about work becoming dehumanizing, but today the bigger fear might be a world where work disappears and that itself feels dehumanizing.

At the same time, the mediating role of decision-making agility has also been observed as a missing debate both in theoretical and empirical studies for which this research has made a major contribution. Figure 1 covers the framework as developed and tested under this research.

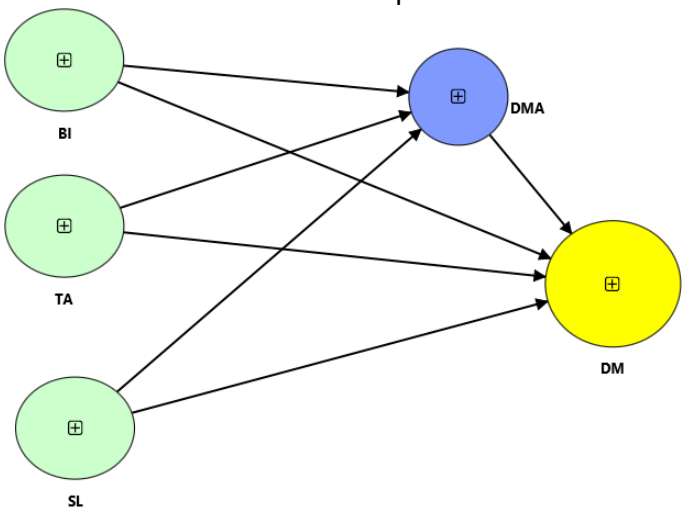

Fig.1: Framework of the study
BI; business intelligence, DM; decision making, DMA decision making agility, SL; strategic learning, TA; technology anxiety.

Moreover, the impact of technology on the decision-making capabilities of the human is not something which can be neglected. For this purpose, Darioshi and Lahav [6] look at how technology shapes the way people make choices, from a behavioral economics point of view. Around the world, there are various firms which offer tools, platforms, devices, search engines, and so on that promise to guide a person through the different stages of deciding, while still leaving the final call to the human. However, one concept is that these tools can help people make smarter and better-informed choices, but they can also open the door to a bunch of decision biases. Their study goes over the main things that trigger these biases when people use technology, and we set out a simple theoretical model to judge when technology is useful for making decisions. Then we show how the model works

by applying it to four well known products: Google, ProQuest, Mobileye, and Waze. Overall, the model adds to what we know about how technology affects human decision making, and it gives a solid starting point for future work on the topic. Besides, there are some several other studies who have considered the factors like strategic learning [9; 10; 31], technology anxiety [14; 27], business intelligence [3; 25; 26], yet these studies are completely missing while focusing on the strategic decision making for the IT firms in Iraq, hence reflecting a good literature gap to fil.

3. Research Methods

Table 1 below reflects the variables under consideration along with the sources. For measuring these items, five points likert scale have been used. After the development of the questionnaire,

Table 1
variables under consideration

Construct	Item (statement)	Source
Business Intelligence	The response rate of the system Easy to use. The system provides interactive reporting The features are useful	Peters et al. [20]
Technology Anxiety	I feel apprehensive about using the BI system I hesitate to use BI technology for fear of making mistakes that I cannot correct I am afraid that the equipment may suddenly stop functioning	Tsai et al. [28]
Strategic Learning	*We are good at identifying strategies that did not work.* *We are good at pinpointing why unsuccessful strategies did not work.* *We learn effectively from our strategic and competitive mistakes.* *We regularly adjust our business practices and competitive tactics as we see what works and what does not.* *We can change our business strategy midstream when we sense how effective our actions will be.* *We recognize alternative approaches to achieve our objectives when it becomes clear the initial approach will not work.*	Garrett et al. [8]
Strategic Decision-Making	Our major operating and strategic decisions result from consensus-oriented decision making Our major operating and strategic decisions are made by single individuals with responsibility in the decision area Our business unit's philosophy is to involve all levels of management in major operating and strategic decisions Consensus seeking is a common and pervasive decision-making practice in my business unit Information and power are shared extensively in making decisions in my business unit	Covin et al. [5]
Decision-Making Agility	The organization collects information from diverse sources before making decisions Strategic decisions by top management lead to restructuring of organizational levels The organization has predetermined plans to face potential financial crises The organization analyses critical events quickly The organization maintains a dedicated database to support the decision-making process The decision-making process adopts alternative strategies when appropriate	Salahat [22]

Note: italic items are slightly modified, rest are the same from the sources

After the researchers have finished designing the questionnaire, we shared it with managers and decision makers in more than 20 top IT companies across Iraq. In total, 350 questionnaires were sent out using a mix of approaches: in-person visits to company offices, outreach through professional networks, and email via company contacts. We received 289 back. After checking each response for completeness and accuracy, 274 were judged valid and used in the analysis. This gave us a solid response rate and a sample that reflects the IT sector fairly well. For the analysis, we used Partial Least Squares Structural Equation Modeling (PLS-SEM), starting with the measurement model and then moving to the structural model. The measurement model was evaluated for reliability, convergent validity, and discriminant validity to make sure the constructs were sound, and the items

really captured what they were supposed to measure. After the measurement model met these standards, we estimated the structural model to test the hypothesized links among the constructs. Finally, SEM results were used to assess the strength, direction, and significance of relationships, providing a clear picture of the overall framework.

4. Findings and Discussion

We have reported the reliability and convergent validity below in Table 2. It represents different variables in the first column, followed by alpha values composite reliability, and amount of average variance extracted, respectively. As the results are reported, alpha scores are 0.725 for BI, 0.915 for DM, and 0.841 for DMA, with 0.747 for SL and 0.876 for TA. Composite reliability (rho_c) is 0.851 (BI), 0.937 (DM), 0.878 (DMA), 0.856 (SL), and 0.913 (TA)—all above the 0.70 threshold. Average variance extracted (AVE) is 0.744 (BI), 0.747 (DM), 0.548 (DMA), 0.665 (SL), and 0.779 (TA), exceeding 0.50 and indicating convergent validity. Composite reliability (rho_a) values are 1.518 (BI), 0.915 (DM), 0.867 (DMA), 0.758 (SL), and 1.042 (TA). Overall, the constructs exhibit acceptable internal consistency and convergent validity and are suitable for subsequent structural analysis.

Table 2
Measurement Model Assessment

variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.725	1.518	0.851	0.744
DM	0.915	0.915	0.937	0.747
DMA	0.841	0.867	0.878	0.548
SL	0.747	0.758	0.856	0.665

BI; business intelligence, DM; decision making, DMA decision making agility, SL; strategic learning, TA; technology anxiety.

Discriminate validity helps to examine the discrimination between the variables based on their measurement items. As reflected by Table 3 findings, the ratio between DM and BI is 0.070, indicating very low overlap. The HTMT matrix further shows that all inter-construct values are below the conventional thresholds of 0.85 (strict) and 0.90 (lenient): DM–DMA = 0.782 (the highest but still acceptable), DMA–SL = 0.417, DM–SL = 0.448, BI–DMA = 0.163, BI–SL = 0.076, BI–TA = 0.105, DM–TA = 0.184, DMA–TA = 0.161, and SL–TA = 0.278. Collectively, on statistical grounds, these results support discriminant validity among the constructs, with DM and DMA showing the closest relationship yet remaining within acceptable bounds. Figure 2 covers the output for those items having their loadings of above 0.50. The items with lower loading were removed from the model.

Table 3
HTMT results

HTMT	BI	DM	DMA	SL	TA
BI					
DM	0.070				
DMA	0.163	0.782			
SL	0.076	0.448	0.417		
TA	0.105	0.184	0.161	0.278	

BI; business intelligence, DM; decision making, DMA decision making agility, SL; strategic learning, TA; technology anxiety.

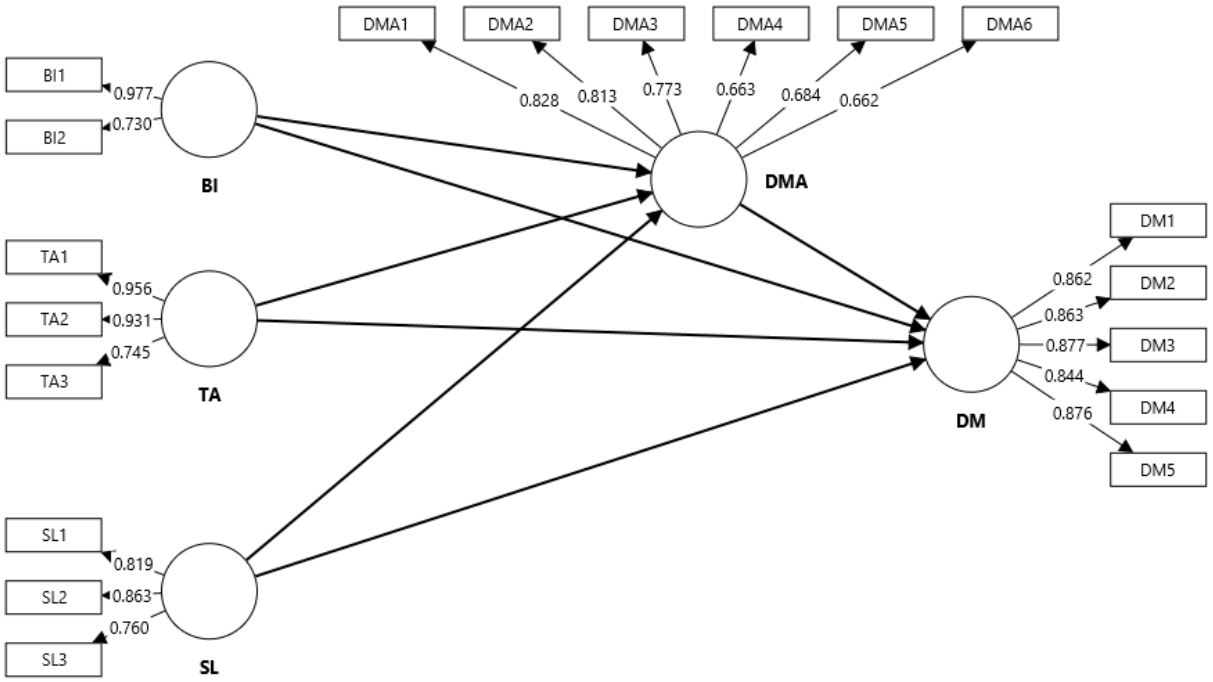

Fig.2: Items' Loadings for the Latent Variables
BI; business intelligence, DM; decision making, DMA decision making agility, SL; strategic learning, TA; technology anxiety.

5. Structural Equation Model Results

Table 4 reflects the direct Path Results of the variables. The structural model indicates that DMA →DM is the dominant predictor of strategic decision making (β eta = 0.694, t-value = 16.486, p-value < .001***). This finding is claiming that as the organizations tend to respond towards the changing market environment, they enhance the quality and effectiveness of their strategic choices. Moreover, agility in the decision-making process enables the business managers to rapidly process the available information, while evaluating some alternative courses of action, for the purpose of timely response. Therefore, such acts thereby help in aligning strategic decisions with dynamic market and organizational conditions.

As the findings report, the connection between BI-DMA is positive and significant (β = 0.151, t = 7.55, p < .001*), while SL shows significant effects on both DM (β = 0.134, t = 2.445, p = .015*) and DMA (β = 0.309, t = 5.414, p < .001*). The findings show that business intelligence is positively impacting on decision making agility, which means when organizations use BI systems effectively, they can move more quickly and flexible in their decision process. BI provides managers with timely and accurate information, and this reduces the time of searching and guessing, so they can act faster and adapt to new changes. In simple words, better BI performance gives the organization the ability to be more agile in handling complex situations. This agility later supports making stronger and more strategic decisions, hence a productive nexus between both exists. In contrast, the direct paths from BI → DM (β = 0.052, t = 0.991, p = .322) and from TA to DM (β = 0.054, t = 1.200, p = .230) and DMA (β = 0.080, t = 1.146, p = .252) are not significant. Conversely, the findings reveal the path from SL to DM is also significantly positive at 5% level. It means that strategic learning is a productive indicator of strategic decision making among the selected organizations. It means that when people in the organization keep learning from past and present things, they take better big decisions for future. Strategic learning makes them more aware about what is going on inside and outside the company, so they not only repeat old mistakes but also find new ways to solve problems. In this way learning becomes a strong sign that the organization will make better choices, because they understand more

and act wiser even if the situation is hard.

Table 4
Direct Path Results

Path Analysis	Original sample	Standard deviation	T statistics	P values
DMA -> DM	0.694***	0.042	16.486	0.000
BI -> DMA	0.151 ***	0.020	7.55	0.000
BI -> DM	0.052	0.053	0.991	0.322
TA -> DM	0.054	0.045	1.200	0.230
TA -> DMA	0.080	0.070	1.146	0.252
SL -> DM	0.134**	0.055	2.445	0.015
SL -> DMA	0.309***	0.057	5.414	0.000

BI; business intelligence, DM; strategic decision making, DMA decision making agility, SL; strategic learning, TA; technology anxiety.

Regarding the specific indirect effects, the findings have been covered in Table 5 which is also known as mediation output. As the results shows, the path of SL -> DMA -> DM is showing a coefficient of 0.215 which is highly significant at 1%, reflecting that there is a significant mediating role of decision-making agility on the relationship between strategic learning and strategic decision making. The results show that decision-making agility acts like a bridge between strategic learning and strategic decision-making. When an organization learns from its experiences, training, and environment, that knowledge makes it quicker and more flexible in responding to new situations. This ability to move fast and adjust helps managers turn what they have learned into better choices for the future. In simple words, learning on its own is useful, but it becomes much more powerful when it also makes the organization agile, and that agility is what finally improves the quality of strategic decisions. However, the results reflect no significant specific indirect effect in terms of the path TA -> DMA -> DM.

Table 5
Mediation Analysis

Specific Indirect Paths	Original sample	Standard deviation	T statistics	P values
SL -> DMA -> DM	0.215***	0.039	5.503	0.000
TA -> DMA -> DM	0.055	0.049	1.132	0.258
BI -> DMA -> DM	0.105***	0.026	4.038	0.000

BI; business intelligence, DM; decision making, DMA decision making agility, SL; strategic learning, TA; technology anxiety.

Lastly, the results are confirming that the path from BI to DMA and from DMA to DM is also positively significant at 1%, reflecting that the there is a significant mediating role of decision-making agility on the relationship between BI and strategic decision making among the targeted firms in Iraq. The findings clearly show that decision-making agility or DMA plays an important mediating effect in reflecting how learning and intelligence turn into better decisions. More on specific grounds, for strategic learning, the indirect path through agility is strong and highly significant. This path clearly indicates that when firms learn and build knowledge, it only translates into effective decision-making if they are also quick and flexible in acting on that knowledge. In the same way, business intelligence on its own does not directly shape strategic decisions, but when it improves decision making under the shadow of agility, it helps managers make stronger and more adaptive choices among the available opportunities. On the other hand, technology anxiety does not show any meaningful indirect effect, which suggests that being worried about new systems neither helps nor blocks agility in a way that matters for decisions. Together, the given results are confirming results underline that agility is the real role player that allows learning and intelligence of the business organizations in Iraq

to flow into higher-quality strategic decisions.

6. Conclusion and Policy Suggestions

This study has been set out to explore how business intelligence, strategic learning, and technology anxiety are going to shape the decision-making process in Iraqi IT firms, with decision-making agility placed as a core mediator. The analysis mainly showed that decision-making agility is the strongest predictor of decision quality, reflecting its crucial role in translating information and knowledge into timely decisions for the selected IT firms in Iraq. Moreover, strategic learning was found to have both direct and indirect effects, meaning that when firms can learn from their past actions and mistakes, they are more agile and ultimately make better decisions. Additionally, the factor like business intelligence also showed an indirect influence, confirming that while BI systems alone do not guarantee better decision outcomes, they provide an important base when aligned with the decision-making agility of the similar firms. Interestingly, technology anxiety did not show significant impact, which suggests that fears about BI tools are less relevant in this context. Overall, the findings underline that learning and intelligence matter, but their true value is realized through agility, which acts as the key link between resources and results.

For IT firms in Iraq, these results offer several practical lessons for different stakeholders including the core decision makers for the same industry. First, managers should not only invest in BI systems but also ensure they are used flexibly and integrated into everyday decision-making practices. Meanwhile, building and establishing some sort of strong mechanisms for strategic learning is equally important, as the IT firms that systematically reflect on what works and what fails are better positioned to adapt to the changing market dynamics. The study also suggests running practical training, so people feel more comfortable with new technology and advancements. Even though anxiety wasn't a big issue in our results, cutting down fear can still help more folks use the tools. Management should also push for teamwork and open talk across departments, because quick, agile decisions only happen when the right information moves easily to everyone who needs it.

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