The Effect of Data Characteristics and Top Management Characteristics on Decision Making Capabilities: The Role of AI and Business Analytical Capability

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Abstract: - Data is essential for making decisions. However, these data should be appropriately collected and analyzed by capable managers. Few studies examined the effect of data characteristics (DC) and top management characteristics (TMC) on decision-making capability (DMC). In addition, few examine the application of artificial intelligence enterprise resource planning (AIERP) in this process. The purpose of this study is to examine the effect of DC and TMC on DMC. Building on existing theories and studies, this study proposed that DC (data integrity, data quality, data authentication, and data error) significantly affect the DMC. In addition, TMC (data analytical capability and technological innovation) significantly affect the DMC. AIERP is predicted to have a mediator role between DC and TMC, and DMC. Business analytical capability (BAC) is anticipated as a moderating variable. The data was collected from technological companies in the Gulf Cooperation Council (GCC). A purposive sampling technique was deployed. The findings using SmartPLS 4.0 showed that DC and its components expect data authentication and TMC and its components have significant effects on DMC. AIERP mediated the effect of DC and TMC on DMC while BAC did not moderate the effect of DC and TMC on DMC. Decision-makers have to focus on collecting high-quality data and ensuring the data is free from error. Decision-makers also have to use technology to enhance the quality and effectiveness of decisions.

Key-Words: - Data Characteristics, Top management Characteristics, Decision making, Enterprise resource planning, Artificial intelligence, GCC, Technological

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1. Introduction

Decision-making is a fundamental aspect of business organization. It has the capability in achieving competitive advantages by making decisions to create new products or services or entering a new market, [1]. Managers with decision-making capabilities (DMC) are able to lead organizations in highly competitive industries and are able to make the right decision during times of uncertainty, [2]. The current environment is characterized by high uncertainty and the need for decision-making is critical for the survival and thriving of organizations. Certain characteristics are required to be held by managers to face the increasing uncertainty, [3]. This can be divided into business analytical capabilities and the ability to interpret data. Due to the use of big data, the size, accuracy, and the possibility for data error, [4], decision-makers have to be aware of the data analytical capabilities and have to use supporting technologies that can help in making decisions, [5].

Developing decisions based on data is deemed beneficial. It is known in decision-making that accurate data leads to accurate information which in turn leads to better decision-making, [6]. A good data characteristic (DC) is integrity, free from error, high quality, and authenticity. A report by McKinsey, [4], indicated that benefits are accruing to companies that base their decision-making processes on ever-increasing amounts of data. According to research conducted by McKinsey, [4], data-driven businesses have a 23 times greater chance of outperforming their competition in terms of client acquisition, a nine times greater chance of retaining consumers, and up to 19 times greater potential for profit, [7]. Therefore, the necessity of maintaining the accuracy of data cannot be stressed because there are many things that depend on the power of data. A single mistake in a dataset might cause a domino effect and affect the decisions that are most crucial to organizations, [8].

Managers with knowledge in the business can use this knowledge in making decisions that can improve the achievement of organizations, [2]. Managers' characteristics such as their knowledge of the industry as well as their innovation capabilities are critical components for decision-makers and the desire to use technical support for making decisions, [2], [9]. Technology such as artificial intelligence (AI) aids decision-makers in effectively addressing and coping with the present business difficulties, [10]. With the advance of technology, decision-making is much based on the technology that is being used. Software such as enterprise resource planning (ERP) and AI provide assistance for decision-makers to make accurate decisions, [11]. AI is transforming the ERP and making it more capable of analyzing data and making decisions, [11].

Nevertheless, there are several issues faced by organizations in using these technologies. One of the issues is related to the knowledge of managers and their innovative capabilities as well as the cost of acquiring this software. Further, the usage of these technologies varied among countries. Developed countries deployed these technologies while there is less usage of the technology in developing countries. In the Gulf Cooperation Council (GCC), technological companies have started deploying these technologies. However, it is not known how the user can affect the decision-making process among these companies. Accordingly, this study aims to examine the effect of DC and top management characteristics (TMC) on the decision-making in GCC technological companies. The study also aims to examine the mediating role of AIERP and the moderating role of business analytical capabilities. The remaining sections of this article are the literature review, research methodology, findings, discussion, implications, and conclusion, respectively.

2 Literature Review

This section presents the theoretical framework as well as the development of hypotheses.

2.1 Theoretical Framework

Several theories can be used to explain the decision-making process. One of these theories is the resource-based view (RBV). This theory suggested that a company can create a competitive advantage and improve decision-making by deploying its resources and capabilities such as top management analytical capabilities and the technological infrastructure, [12]. The technology-organization-environment framework (TOE), the framework suggested that there are organizational and technological aspects that affect the decision-making to use new technology. The technological aspect is related to the technological characteristic such as the mechanism of having accurate, integrated, authenticated, and free-from-error data. In addition, it is related to the use of technological tools such as AI and ERP. Building on these two theories, this study is deploying the conceptual framework.

2.2 Critical Analysis

In this study, certain variables are deployed to enhance the DMC of managers and decision-makers in technological companies in GCC. The variables include the DC which includes the data integrity (DI), data quality (DQ), data authentication (DA), and data error (DE). In addition, the variables also include the TMC which includes the data analytical competency (DAC) and technological innovation (TI). The study also includes the variable of AIERP and business analytical capabilities (BAC). In Table 1, the prior literature is examined to understand how these factors can affect the DMC and to identify the gaps in the literature.

Table 1. Critical Analysis for Selected Variables

Variables/ studies	DC	DI	DQ	DA	DE	TMC	DAC	TI	AIERP	BAC
[13]	✓								✓	
[14]			✓						✓	
[15]	✓					✓			✓	
[16]			✓			✓			✓	
[17]	✓					✓				
[18]	✓					✓			✓	
[19]			✓			✓			✓	
[20]								✓		
[21]		✓	✓	✓	✓					
[22]										✓
[23]							✓			
[24]							✓			

As shown in Table 1, none of the reviewed studies have included all the selected variables. Some variables such as DAC have received less attention compared with DC. In this study, these variables are included.

2.3 Conceptual Framework and Hypotheses Development

Building on the theory of RBV as well as the TOE, this study assumes that the effects of variables such as DC and TMC on DMC are positive. The research also predicted that the effect of both the DC and TMC is mediated by AIERP and moderated by the business analytical capabilities. Figure 1 shows the conceptual framework.

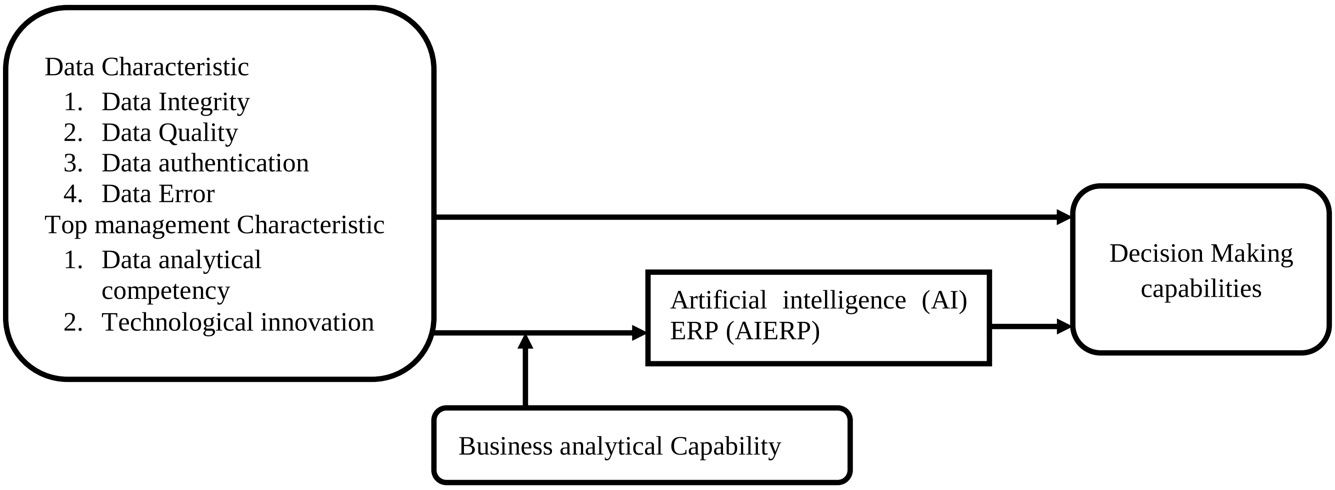

Fig. 1: Conceptual Framework

2.3.1 DC

DC is defined as the traits of data of being accurate, reliable, having high quality, and free from error, [25]. In this study, DC is a second-order variable, and it consists of data integrity, data quality, data authenticity, and data error. Prior literature indicated that the data is essential for making decisions, [6]. Having accurate, reliable, and free-of-error data will enable companies to achieve competitive advantages by making the right decision, [7]. Therefore, it is proposed that:

H1: DC has a positive effect on DMC.

2.3.2 Data Integrity

In the context of the data lifecycle, data integrity is described as "the extent to which all data are full, consistent, and correct at all times", [26]. The procedures of cleaning, mining, analysis, and other processing of big data are significantly influenced by data integrity in a number of ways, [27]. Data integrity is linked positively to the business to business transactions, [28]. It also has a positive impact on the decision to use internal banking, [29]. Data integrity has also a positive effect on customer trust in online banking, [30]. In this study, data integrity is expected to affect the DMC of managers and directors of technological companies in GCC.

H2: Data integrity positively affects the DMC.

2.3.3 Data Quality

The term "data quality" refers to the dependability and the application efficiency of the data that is currently available in a system, [31]. Data quality affected positively the decision-making system, design, and validation, [32]. In addition, data quality also affected the business operation, [33] as well as the performance of a machine learning system, [34]. Therefore, this study proposes a positive link between data quality and DMC by managers of technological companies in GCC.

H3: Data quality positively affects the DMC.

2.3.4 Data Authentication

The authenticity of data is defined as the maintenance of the data's integrity in addition to the possibility of origin verification, [35]. The legitimacy of the data is the most important factor in determining the quality of the data. Data authentication has an impact on the quality of decision-making, which, in turn, has an impact on the success of businesses, [36]. Data authenticity affected the decision to use the internet of things (IoT), [37]. In this study, data authenticity is proposed as a predictor of the DMC of managers in GCC technological companies. Therefore:

H4: Data authenticity positively affects the DMC.

2.3.5 Data Error

It is not uncommon that there are mistakes made as a result of the loss of some data, particularly crucial data, [27]. Data error affects decision-making and leads to misleading decisions, [2]. Error in data can lead to poor-quality decision-making, [36]. Data error can cause loss or damage of information which leads to less quality decision-making, [37]. Accordingly, in this study, data error is expected to have a negative effect on the DMC of managers in GCC.

H5: Data error has a negative effect on the DMC.

2.3.6 TMC

TMC is defined as the competency and the skills of the top management that helps in making a decision, [38]. TMC has a significant effect on several organizational outcomes such as organizational innovation and business process development, [39]. TMC affected positively rational decision-making, [40]. TMC also affected the firm performance, [41]. TMC is proposed in this study as a predictor of the DMC. Therefore, the following is hypothesized:

H6: TMC positively affects the DMC.

2.3.7 Data Analytical Competency

A manager's data analytical capability (DAC) is a broad description of their expected level of know-how and ability in this area, [42]. DAC is critical for decision making and it is found to have a significant effect on the DMC, [24]. DAC also positively affected the decision-making quality, [42]. The decision-making quality is also affected by DAC, [43]. This study proposed that DAC will affect the DMC by managers of GCC in technological companies.

H7: DAC positively affects the DMC.

2.3.8 Technological Innovation

In business, technological innovation refers to the introduction of novel methods, apparatuses, and materials that improve upon previous practices by increasing productivity and efficiency. Technological innovation positively affected the DMC, [44]. Technological innovation affected the decision to use green productivity, [45]. It also affected the decision to introduce new technology in organizations, [46] and the technology energy efficiency in the organization, [47]. In this study, technological innovation by managers is expected to have a significant effect on the DMC of technological companies in GCC.

H8: technological innovation positively affects the DMC.

2.3.9 Mediating Role of AIERP

The use of technology such as AI and its combination with ERP has enhanced the DMC of managers. ERP positively affected business model innovation, [48]. Additionally, it has mediated the relationship between the performance of SMEs and internal and external elements (technical development, government policy, information access, organizational culture and structure, communication process, and IT readiness), [49]. In India, the adoption of AI-CRM moderated positively the effect of digital transformation on the entrepreneurship process of SMEs, [50]. In this study, the usage of AIERP is expected to mediate the effect of DC and TMC on the DMC of managers in technological companies in GCC.

H9: AIERP mediates the effect of DC on DMC.

H10: AIERP mediates the effect of TMC on DMC.

2.3.10 Moderating the Role of Business Analytical Capabilities

Business analysis is essential for making decisions. Business analytical positively affected the firm performance, [51]. Business management capabilities and technology capabilities moderated the effect of business model novelty and efficiency design with new product development performance, [52]. Business analytical capabilities moderated the effect of intelligence dissemination and responsiveness of managers, [53]. In this study, the business analytical capabilities of managers of technological companies in GCC are expected to have a moderating role between the DC and the TMC and their impact on DMC. Therefore, the following is proposed:

H11: BAC moderates the effect of DC on DMC.

H12: BAC moderates the effect of TMC on DMC.

3 Research Methodology

This study aims to examine the effect of DC and TMC on the DMC of technological companies in GCC. Therefore, the population of this study is the technology companies in GCC which includes six countries. The number of technology companies is 1,754 companies, [54]. These companies are the population of the study, and they are represented by their managers, executives, and directors. All the companies are large-scale companies, and they have the potential to use advanced technology such as AIERP. However, due to the lack of knowledge regarding the capabilities of these companies and contact details, purposive sampling is deployed in this study. This is because the study set criteria to ask only those who deploy the AIERP and to ask only managers or top management-level employees. Therefore, a question is asked at the beginning of the online questionnaire regarding the usage of AIERP. Those who have the technology are only asked to answer the questionnaire.

The variables of the study were adopted and self-developed. The adopted variables are data integrity (4 items), data authentication (4 items), data error (4 items), and data quality (5 items) were adopted from, [25], [38]. TMC which includes the data analytical capabilities (6 items) adopted from, [52] and the technological innovation (4 items) adopted from, [55]. DMC consists of 8 items and it was adopted from, [52]. Business analytical capabilities and AIERP was self-developed based on prior literature that has deployed similar variables such as [50], [51], [52], [53]. The questionnaire was validated by three experts in information technology and decision-making. A pilot study was conducted on 34 top management employees that are not included in the field data and the reliability of the measurement was established because Cronbach's Alpha (CA) is greater than 0.70 and this meets the assumption of the reliability, [56].

The data was collected from 315 managers and executives in the GCC technological and information technology companies. The data collection took place between December 2021 and April 2022. The data were checked for missing values and outliers. This has resulted in removing 13 responses. Further, the normality was assessed using Skewness and Kurtosis. All values are less than 1 and this meets the assumption of normal data distribution. The multicollinearity was not an issue in this study because the value of variation inflation factor (VIF) and tolerance (T) is less than 5 and greater than 0.20 respectively as shown in Table 2.

Table 2. Result of Normality and Multicollinearity

Variable	N	Skewness	Kurtosis	Tolerance	VIF
Data Integrity	302	-.068	-.481	.796	1.257
Data quality	302	-.531	-.344	.635	1.575
Data error	302	-.660	-.412	.362	2.764
Data authentication	302	-.720	-.473	.332	3.012
Data analytical capability	302	.503	-.533	.640	1.561
Technological innovation	302	-.773	-.068	.454	2.201
AIERP	302	-.409	-.544	.276	3.618
Business analytical capability	302	-.842	-.089	.302	3.311
DMC	302	-.625	-.227	-	-

4 Findings

4.1 Background of the Respondents

This study included 302 respondents. The background of the respondents is shown in Table 3. The majority are males (78.1%), with ages older than 35 years (79.1%) and education of bachelor's degree and above. The respondents have experience of more than 5 years (97%).

Table 3. Background of Respondents

Variable	Label	Frequency	Percent
Gender	Male	236	78.1
	Female	66	21.9
Age	26-35	72	23.8
	36-45	108	35.8
	More than 45	122	40.4
Education	First university degree	232	76.8
	Postgraduate	70	23.2
Experience	Less than 5 years	9	3.0
	6-10 years	101	33.4
	11 to 15 years	138	45.7
	16-20 years	37	12.3
	More than 20 years	17	5.6

4.2 Measurement Model

SmartPLS 4.0 was used to analyze the data for this investigation, and the measurement model was evaluated by examining the factor loading (supposed to be more than 0.70), Cronbach's Alpha (CA), composite reliability (CR), and validities, including convergent and discriminant validity. To increase the validity and reliability, several items were removed. The values of CA, CR, and convergent validity were attained, as shown in Table 4. Because the average variance extracted (AVE) was more than 0.50, the convergent validity was satisfied.

The discriminant validity was met because the indicators are greater than the cross-loading of the variables as shown in Table 5.

Table 4. Results of Assessing Measurement model

Second order	Variables	CA	CR	AVE
AIERP	AIERP	0.947	0.954	0.862
Business analytical capability	Business analytical capability	0.962	0.963	0.840
Data analytical capability CA=0.845 CR=0.851 AVE=0.593	Data Authentication	0.702	0.921	0.648
	Data Error	0.612	0.570	0.294
	Data Integrity	0.722	0.930	0.681
	Data Quality	0.910	0.920	0.736
TMC, CA=0.899, CR=0.901, AVE=0.671	Data Analytical Capability	0.943	0.945	0.814
	Technological Innovation	0.741	0.710	0.579
DMC	DMC	0.925	0.926	0.817

Table 5. Discriminant Validity

	AIERP	BAC	DAC	DA	DE	DI	DQ	DMC	TI
AIERP	**0.929**								
BAC	0.543	**0.916**							
DAC	0.432	0.488	**0.902**						
DA	0.590	0.602	0.515	**0.805**					
DE	-0.557	-0.570	-0.594	-0.613	**0.843**				
DI	0.546	0.585	0.550	0.552	-0.515	**0.825**			
DQ	0.462	0.471	0.527	0.458	-0.462	0.539	**0.858**		
DMC	0.578	0.614	0.648	0.554	-0.658	0.646	0.625	**0.904**	
TI	0.540	0.561	0.546	0.478	-0.484	0.637	0.595	0.674	**0.892**

4.3 Structural Model

The assessment of the structural model includes the R-square (R^2) which represents the explanatory power of the models. The value for the direct effect models was 0.57 indicating that DC and TMC can explain 57% of the variation in DMC. In the mediating model, the value increased to 0.59 indicating that adding BAC can increase the variation in DMC. Further, the R^2 increased to 0.62 in the moderation model which added to the explanation of the DMC. The F-square is acceptable for all paths except for Data Authentication -> DMC and the moderation paths. The structural model of this study is presented in Figure 2. The Figure shows the mediation and the moderation model.

The results of testing the hypotheses are shown in Table 6. All the hypotheses related to the DC except data authentication are significant. Similarly, the hypotheses related to TMC are significant as well as the mediator. However, no moderating effect of BAC was identified in this study.

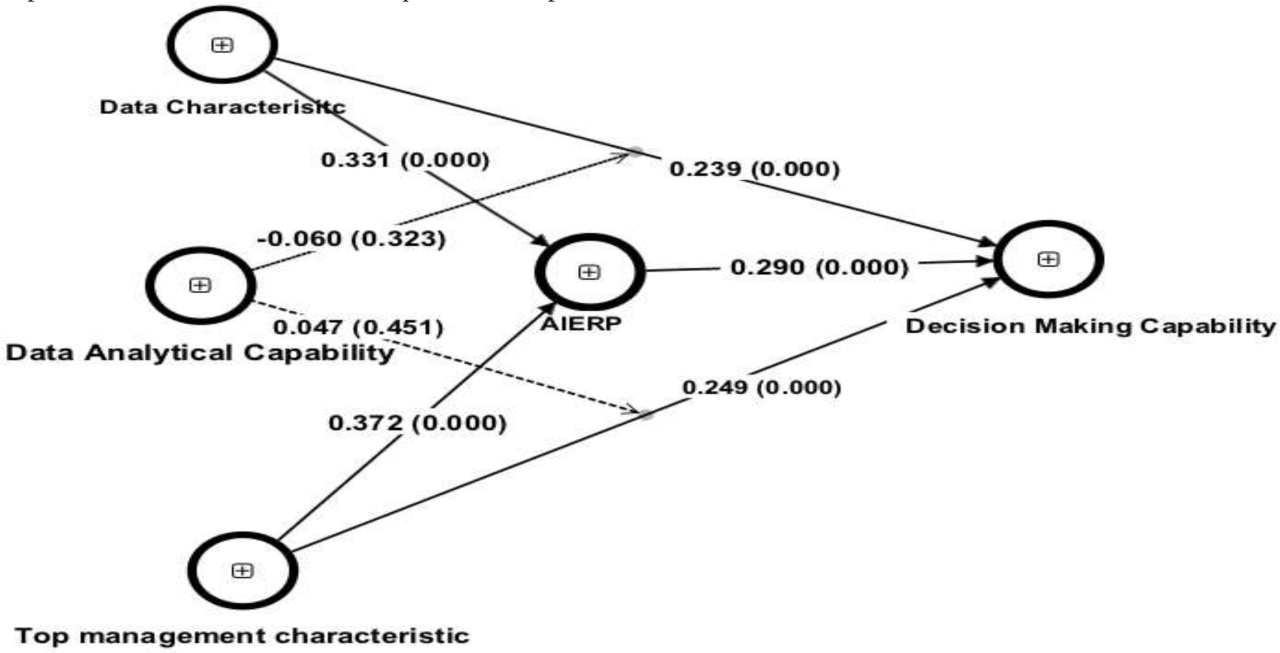

Fig. 2: Structural Model

Table 6. Results of the Hypotheses

Hypothesis	Path	B	Std.	T	P	Remark	R^2	F^2
Direct Effect								
H1	DC-> DMC	0.390	0.056	7.012	0.000	Sig	0.57	0.08
H2	Data Integrity -> DMC	0.158	0.044	3.565	0.000	Sig		0.03
H3	Data Quality -> DMC	0.176	0.041	4.271	0.000	Sig		0.04
H4	Data Authentication -> DMC	0.022	0.053	0.417	0.677	Not sig		0.00
H5	Data Error -> DMC	-0.267	0.058	4.570	0.000	Sig		0.06
H6	TMC->DMC	0.437	0.052	8.445	0.000	Sig		0.13
H7	Data Analytical Capability -> DMC	0.169	0.084	2.014	0.044	Sig		0.08
H8	Technological Innovation -> DMC	0.237	0.049	4.853	0.000	Sig		0.10
Mediation								
H9	DC->AIERP->DMC	0.107	0.043	2.463	0.014	Sig	0.59	0.03
H10	TMC->AIERP->DMC	0.120	0.043	2.825	0.005	Sig		0.04
Moderation								
H11	BAC x TMC -> DMC	0.047	0.063	0.755	0.451	Not sig	0.62	0.00
H12	BAC x DC -> DMC	-0.060	0.061	0.988	0.323	Not sig		0.00

The first hypothesis related to the DC was confirmed because the effect of DC on DMC is significant at 0.000 supporting H1. For H2, H3, and H5, they are supported because the p-value is less than 0.05. Thus, data integrity, data quality, and data error are critical for decision-making. However, data authentication is not important because the p-value is greater than 0.05. Thus, H4 is rejected. This could be related to the notion that the data is prepared in the organizations. For the effect of TMC on DMC, the findings in Table 6 showed that there is a positive relationship. Similarly, for H7 and H8, the effects of BAC and TI are significant. The mediation effect was examined by using the specific indirect effect provided by SmartPLS 4.0. The business analytical capability mediated the effect of DC on DMC and this supports H9. Similarly, the H10 is supported because the direct and indirect effect of TMC on DMC is significant directly and via the mediator AIERP. Thus, H10 is supported. The moderation effect of AIERP was found not significant. The moderator was examined using the product indicator approach as suggested by, [56]. BAC did not moderate the effect of DC on DMC or the effect of TMC on DMC. Thus, H11 and H12 are rejected.

5 Discussion

This study examined the effect of DC and TMC on the DMC among technology companies in GCC. The findings showed that both the DC and the TMC are critical for the DMC. TMC is more critical compared with DC because the coefficient is higher than the DC. However, both characteristics are critical for DMC. These findings are in line with the RBV which indicated that using the resources and capabilities of companies can lead to competitive advantage which ultimately leads to better performance, [12]. In addition, the TOE pointed out that the decision of using innovation is dependent on technological factors such as the DC and its components. The findings also agree with the findings of, [25], [7] in terms of the effect of DC on DMC. The findings of prior literature indicated that the effect of TMC on DMC is positive, [39], [41].

In terms of the components, the most critical components are data errors. Error in the data can lead to a vital effect on the DMC. Wrong data leads to wrong and misleading decisions which might affect the performance of technological companies. These findings in line with the report of, [7] which indicated that decision-based on accurate data is critical for the effectiveness of decision-making. The second important components of DC are data quality followed by data integrity. These findings are in line with prior literature because the high quality and integrity of data lead to better decision-making [29], [30], [32], [33], [34].

For the TMC, the effect of DAC on decision-making is important, indicating that managers with high DAC will make more accurate decisions. This finding is in agreement with the findings of, [24] who found that DAC has a positive effect on decision-making. In addition, technological innovation is critical for the DAC indicating that managers with high technological innovation will make decisions accurately. The findings of prior literature agree with the findings of this as they found that technological innovation is important for the decision to use green products, the introduction of new technology in the organization, and the use of technology effectively, [45], [46], [47].

The mediating role of AIERP was confirmed in this study. This mediation is partial which indicates that part of the relationship between DC and DMC as well as between TMC and DMC can be explained by the AIERP. This indicates that using the AIERP can help greatly in making the decision by technological companies in GCC. These findings are in line with the findings of previous studies such as, [49] which found that internal and external factors can be mediated by ERP. Lastly, the moderating effect of BAC was not confirmed in this study. This might be due to the notion that this software helps more in providing information for decision-making where the need for the managers' capabilities is reduced.

6 Implications

This study has examined the effect of DC and TMC on DMC. The findings referred to the importance of both characteristics. Decision makers in the GCC must focus on the capabilities of managers in making decisions. The ability to understand the data and interpret data in a scientific manner can help in making accurate and effective decisions. Data error is catastrophically harmful to decision-making. Therefore, decision-makers have to make sure that the data is accurate and free from error. This can be ensured by paying attention to the quality of data as well as its integrity. The findings also showed that technological innovation is important for decision-making. Policymakers should focus on selecting managers who have high technological innovation and are open to the usage of new technology that can help in forming better decisions that will have an impact on decision-making. The use of AIERP is critical for organizations to identify errors and make decisions using advanced technology. Decision makers have to launch training courses to enhance the knowledge of managers regarding the usage of AIERP. Having adequate knowledge will enhance technological innovation which will lead to more usage of advanced technology and ultimately lead to enhanced decision-making.

Business analytical capability did not moderate the effect of DC and TMC and this could be due to the fact that this study selected companies that have ERP systems which mean that the knowledge of business analytics is similar among the respondents. This might explain the insignificant effect. However, those in the position of developing the policy are advised to conduct an assessment of the understanding of managers regarding the industry and choose those who have a high level of knowledge. This study has contributed to the literature by examining the DC and TMC in the context of GCC. This research added to the existing body of knowledge by investigating the moderating effect of BAC and the mediating effect of AIERP. Another contribution was made by integrating the RBV and the TOE in the context of decision-making. This integration has helped in explaining a large portion of the variation in decision-making.

7 Conclusion

This study was conducted to examine the DMC of managers in technological companies in GCC. Managers should understand the importance of the DC and its components. TMC is critical when it comes to making decisions in a highly competitive market. Using technology such as AIERP will give companies a competitive advantage and enhance their ability to make decisions. The study was conducted on technological companies in GCC using the information provided by the top management of these companies. In addition, the study deployed purposive sampling. Thus, the study is limited to the companies that have participated in this study. To extend the findings of this study, future work is recommended to examine the effect of DC and TMC in other industries such as the service industry or manufacturing industry. Future work is advised to focus on other emerging economies. Future studies also are advised to include other variables such as technological uncertainty. Control variables such as age and size of the company as well as the cost of using technology can be employed by future research to explain decision-making. It is advised for decision-makers to train senior management staff members and expand the use of cutting-edge technologies to improve DMC.

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