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Learning, Integration, and Re-Configuration: Dynamic Capabilities as Drivers of Data-Driven Insights and Decision Quality

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Abstract

The study investigates the role of the dynamic capabilities of learning, integration, and re-configuration on the quality of decision-making mediated by data-driven insights. It particularly examines how these dynamic capabilities individually contribute to offering efficient and effective decision-making in the hospitality sector. This study employs a quantitative research approach harnessed through surveys and the application of partial least square structural equation modelling using SMART PLS 4. The hospitality sector being a highly competitive industry was selected for data collection. The findings reveal that learning and reconfiguration capabilities have a significant positive individual impact on generating data-driven insights hence improving the effectiveness and efficiency of decision-making. Contrarily, the integration capabilities standalone did not influence in pointing out the statistical significance of the relationship with data-driven insight or decision-making quality, an indication that integration has to be combined with other dynamic capabilities for it to be effective. This study adds novelty to the literature by examining the individual influences of dynamic capabilities—learning, integration, and reconfiguration on data-driven insights and decision-making quality. Unlike previous studies that have generally explored bundles of capabilities, this study isolates each to answer the more nuanced question of how organizations can, in a strategic manner, invest in certain dynamic capabilities that can improve decision-making.

Keywords: Dynamic capabilities, learning capabilities, integration capabilities, data insights, decision quality

INTRODUCTION

The big data revolution has challenged the global business environments influencing organizations to evolve in technology adoption and related expertise. At the same time, it offers opportunities to enhance decision-making quality by leveraging humongous data resources allowing more informed and accurate decisions(Niu et al., 2021). Decision quality is crucial for achieving organizational goals such as competitive advantage, performance, innovation, etc. Decision-making effectiveness can be strengthened when there is an improvement in an organization's capabilities to acquire, analyze, and utilize information and knowledge resources(Shamim et al., 2019). Dynamic capabilities aid decision-making by swiftly sensing, seizing, and adapting to environmental changes to strategically align the decisions (Pavlou & El Sawy, 2011; Shamim et al., 2019). The dynamic capabilities of learning, integration, and reconfiguration nurture data-driven insights by effectively synthesizing big data resources. Such data insights, by offering evidence-based information, reduce uncertainty and biases in the decision process, leading to more informed and effective decisions (Awan et al., 2021). In such data-driven environments, the firms' strategic position and competitive advantage stem from their unique abilities to extract data insights based on which quality decisions are made. Extant literature explores decision-making quality as an essential aspect linked to organizational strategies and outcomes. Following the Dynamic Capabilities View (DCV), organizations operating in dynamic environments need to capitalize on dynamic capabilities instead of banking on ordinary capabilities. Dynamic capabilities such as learning, integration, and reconfiguration, can be critical enabling factors for generating data-driven insights and achieving quality decision-making. Such dynamic capabilities allow firms to learn and update their knowledge and expertise while responding swiftly to environmental changes by integrating new information effectively. Further, the capabilities of reconfiguring enable organizations to meet emerging challenges timely and swiftly.

Literature has discussed dynamic capabilities for their positive influence on corporate sustainability and competitive advantage (Bari et al., 2022), innovation (Farzaneh et al., 2020), and performance (Ferreira et al., 2021), however, meagre research is found on the role of dynamic capabilities of learning, integration, and re-configuration on the decision-making quality and the data-driven insights. Moreover, there is scant research available on the independent role of these dynamic capabilities on decision-making and data insights which is a crucial aspect as these dynamic capabilities are distinct in nature and functionality. The current study fills the gaps by investigating the distinct influence of dynamic capabilities of learning, integration, and reconfiguration in isolation on the generation of data insights and decision-making quality to better understand and prioritize specific capabilities for their influence on data-driven insights and decision-making quality.

Dynamic capability (DC) are defined as the ability to sense and seize opportunities in the changing environment by learning, integrating and, reconfiguring the internal and external resources/competencies (Teece, 2012). The distinctiveness of learning capabilities lies in its obvious abilities to generate knowledge and data insights which may support quality decisions. Integration capabilities combine and channelize information from various internal and external sources thus improving the decision-making. Additionally, the reconfiguration capabilities ensure that decision-making is not only informed but also agile and responsive therefore may impact the effectiveness of decision-making. Dynamic capabilities are path-dependent capabilities nurtured continuously and consistently over a long time which enable agile organizational response to dynamic environmental changes. Data-driven insights, such as descriptive, predictive, and prescriptive, offer actionable intelligence for strategic decision-making. Literature supports the synergistic role between various dynamic capabilities (Eisenhardt & Martin, 2000; Teece, 1997; Teece, 2023); however, it is pivotal to examine their distinct influences on decision-making quality to prioritize investment in different dynamic capabilities.

The role of dynamic capabilities is investigated in the context of the hospitality sector which is particularly facing intense competition in the digital era due to technological transformation (Nikopoulou et al., 2023). The hospitality sector is influenced by the mass scale of data produced by social media networks impacts customer choices and plans on the selection of hospitality nobilities. Therefore, data-driven insights and decision-making quality are crucial for the success and sustainability of the hospitality sector to enhance customer experiences, improve operational efficiency, and maintain competitiveness. The research outcomes will be significant to understanding the synergy between different dynamic capabilities such as learning, integration, and re-configuration and their influence on generating data-driven insights and decision-making quality. This study will contribute to the literature by unfolding the black box of dynamic capabilities (Pavlou & El Sawy, 2011) explaining the individual effects of different dynamic capabilities on organizational outcomes. The findings of this investigation will be particularly beneficial for organizations operating in dynamic environments, especially the hospitality sector. The sector is uniquely affected by a wide range of factors such as economic, social, demographic, technological, environmental, political, cultural, health and safety etc. The research will provide actionable strategies to build data-driven insights and improve decision-making processes to better adapt to a rapidly changing business landscape.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The current study is theoretically anchored in the dynamic capabilities theory (DCT) which advocates the positioning/repositioning of the strategic orientation according to the dynamic changes in the environment. DCT explains how processes, positions, and paths are managed to achieve organizational goals e.g. competitive advantage for the firm (Fainshmidt et al., 2019). While the process refers to the operational routines in the organization, the position depicts the overall current state of the firm's resources and the path denotes the firm's strategic orientation. Dynamic capabilities theory fundamentally provides a strategic orientation to firms to gain competitive advantage through a series of repetitive activities. These activities include learning, integration, coordination, and organization/re-organization of the available resources to proactively cope with the dynamic challenges of the business environment (Teece et al.,1997). In the strategic management literature, the dynamic capabilities theory is a significant extension of the RBV, which is focused on achieving sustainable competitive advantage under intense business competition (Mikalef et al., 2019; Shan et al., 2019). It is a never-ending learning mechanism involving learning and unlearning to gain the effectiveness of organizational processes (Zollo & Winter, 2002).

Dynamic capabilities of learning, integration and reconfiguration enable the organization to gain sound data-driven insights and quality decision-making from big data. These capabilities focus on enhancing learning through knowledge creation and training of employees, which support continuous learning in an organization. Besides learning capabilities, integration capabilities update a firm with information on customer choices, patterns and needs to analyze the evolving market trends. Integration capabilities enhance the decision-making quality by developing internal and external alliances with other organizations. Moreover, the reconfiguration capabilities ensure the flexible and prompt response of the organization towards market changes. Reconfiguration also requires organizations to create new jobs or reorganize old ones to enhance flexibility among their employees, processes and system as a whole.

Prior studies have used the DCT in exploring the association between dynamic capabilities and other organizational outcomes, suggesting the appropriateness of selecting the DCT for the present study (Erevelles et al., 2016). Shamim et al. (2019b) posited that dynamic capabilities derived from big data are knowledge-based dynamic capabilities, which in turn, enable innovation in organizational processes, products and services. The current study advocates those dynamic capabilities of learning, integration, and re-configuration play a valuable role in harnessing up the organizational processes in producing data-driven insights such as descriptive, predictive, and prescriptive insights. These data insights bring good quality decision-making. It proposes that organizations that nurture strong dynamic capabilities in individuals, processes, and structures are in a better position to gain from emerging opportunities and refrain from threats (Wetering et al., 2017; Yang & Gan, 2020). Dynamic capabilities are elements required to develop such resources that are conducive to today's highly competitive global markets. By investing in intangible strategic assets, organizations can enhance their competitive advantage (Chadwick & Flinchbaugh, 2021).

It is more concerned with organizational capacity building by developing novel competencies and integrating them with the current dynamic requirements (Shamim et al., 2019). Therefore, aligning with the DCT, an organization that develops sound dynamic capabilities by including various dimensions such as learning, integration, and re-configuration influences big-data value creation by generating data insights to strengthen the decision-making quality. Big data provides such insights that provide choices based on which decisions are made (Wilden et al., 2013); hence, new processes and products are devised (Pezeshkan et al., 2016); to determine optimal methods to create alignment and realignment between the organization's internal and external resources and the strategy (Teece, 2014). See figure 1 for theoretical framework.

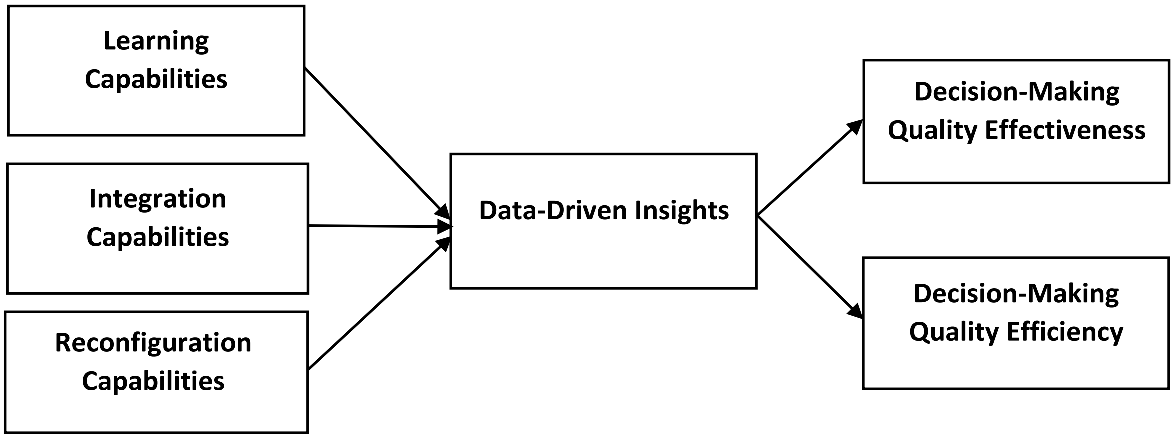

Figure 1.
Theoretical Framework

Dynamic Capabilities

Dynamic capabilities constitute an organization's ability to provide innovative solutions that are adaptive to changes in the market and produce such products/services that satisfactorily meet customer needs (Teece et al., 2016). Dynamic capabilities, therefore, channel the organization's resources and capabilities and integrate the organizational processes with the market changes by sensing opportunities in the environment (da Silva Souza & Takahashi, 2019). Opportunities are captured by continuously scanning, screening and exploring new technologies and market needs (Lütjen et al., 2019). The present study focuses on three capabilities i.e., learning, integration and reconfiguration capabilities. Learning capabilities focus on how easy it is to inculcate learning into the organization's processes (Buzzao & Rizzi, 2021). Integrating capabilities advocates the acquisition of customer data from appropriate markets and identifying new markets. Meanwhile, reconfiguration capabilities enable an organization to reorganize processes or jobs to respond to its competitors well in time. Dynamic capabilities aid in developing a sense of the organization's environment so that appropriate responses can be devised (Zheng et al., 2011). The dynamic capabilities of learning, integration and reconfiguration enhance the firm's ability to sense and seize opportunities, as well as to adapt and realign its functions/operations with the external stimuli. The dynamic capabilities of learning, integration and reconfiguration ensure that responses can be promptly measured to meet and exceed market changes. Teece (2007) advocates the role of dynamic capabilities in achieving organizational outcomes such as efficiency through establishing evolutionary suitability by avoiding unfavorable path dependencies (Teece, 2007).

Dynamic Capabilities and Data-Driven Insights

Dynamic capabilities of learning, integration, and reconfiguration enhance the organization's ability to develop insights from the data. The role of dynamic capabilities is further extended to gain, integrate and reconfigure knowledge and data-driven analysis to extract data-driven insights (Witschel et al., 2019). Dynamic capabilities are core elements required for developing rich data-driven insights by employees engaging in activities such as experimenting with data and contextualizing the data. Therefore, the data is made more meaningful within the bounds of a real-time incident, and subsequently, the data to make decisions that further generate insights on the data acquired from past and present sources (Yang et al., 2019). Dynamic capabilities such as learning, integration, and reconfiguration enhance employees' ability to use data for knowledge creation according to the firm/department's requirements.

Learning is enhanced through conducting training and sharing knowledge, which further enhances data-driven insights (Ghasemaghaei & Calic, 2019). Moreover, integration capabilities involve information about the customers, anticipated market requirements, and need assessments for new products and services based on the insights (Awan et al., 2021). Moreover, reconfiguration capabilities are characterized by reorganizing the internal setups to facilitate a swift and precise response to external changes (Schymanietz & Jonas, 2020). Using reconfiguration, the firm creates an easy channel of communication with the partner companies, thus simplifying the response to external factors. Dynamic capabilities have the potential to generate deep insights by reducing the complexity of the process of extracting data-driven insights (Ghasemaghaei and Calic, 2019).

Data-driven insights are segregated into three categories i.e., descriptive, prescriptive, and predictive, which are the insights that require different dynamic capabilities to extract knowledge from the given big-data resources, incorporate data from multiple sources i.e., customers, competitors, partner firms, market regulation and give meaning to the insights about past data (descriptive), present (predictive- possible future outcomes), and future (prescriptive) insights. Learning capabilities enhance employees' knowledge and understanding through training and sharing enabling them to generate data-driven insights. Similarly, integration capabilities positively and significantly influence data-driven insights by incorporating customer data and market intelligence. Reconfiguration capabilities allow swift changes in organizational structures and processes in response to external changes and market dynamics. Based on the aforementioned, this study hypothesized that:

H1. Learning capabilities are significantly and positively related to the data-driven insights

H2. Integration capabilities are significantly and positively related to the data-driven insights

H3. Re-configuration capabilities are significantly and positively related to the data-driven insights,

Data-Driven Insights and Decision-Making Quality

Knowledge gained through big data received from different data sources adds to the range of data-driven insights extracted. The insights that are genuine and authentic are valuable, thereby assisting the organization to generate quality decision-making. Decisions made thereof are precise and appropriate, which may provide a new solution to organizational issues. The more valuable sources are used to capture data from past, and present trends, the better and more reliable insights (descriptive, prescriptive, and predictive) will be developed. If sources of data are not extensively selected, the data will suffer from incompleteness, and insights built upon incomplete data will be poor, which may harm the quality of decision-making. Dynamic learning capabilities and knowledge sources are prominent factors affecting data insights (Ghasemaghaei et al., 2018). The literature identifies that decision-making is affected by information processing and interpretation of information (Joseph & Gaba, 2020), the dynamic capabilities of learning and integration focus on processing information and interpreting it within the context. Further, big-data management capabilities of contextualization, experimentation and execution are enablers to gain knowledge and develop insights for decision-making. In light of the dynamic capability theory, the present study posits that dynamic capabilities (i.e., learning, integration and reconfiguration) assist in generating data-driven insights, which are beneficial for decision-making quality.
Poor learning capabilities restrict an organization's ability to process information and utilize the full potential of big data resources. By using the data insights, organizations can generate good quality decisions while complying with the dynamic capability view (Awan et al., 2021). The current study aims to examine to what extent data-driven insights mediate the relationship between dynamic capabilities (learning, integration, reconfiguration) and decision-making quality (Grant, 1996). A previous study has documented the use of data-driven insights in exploring the effectiveness of decisions taken at the organizational level (LaValle et al., 2011). Moreover, the mediating role of data-driven insights in big-data innovation is also established (Ghasemaghaei & Calic, 2019). The main stance of this relationship is that the dynamic capabilities developed in the organization will result in decision-making quality. Therefore, it is hypothesized that:

H4. data-driven insights significantly and positively related to the decision-making effectiveness
H5. data-driven insights significantly and positively related to the decision-making efficiency

Data-driven Insights as a mediator between Dynamic Capabilities and Decision-Making Quality

Literature has discussed the mediating role of data-driven insights on decision-making and big data analytics (Awan et al., 2021), therefore, a need to assess the mediating role of data insights between dynamic capabilities such as learning, integration, and reconfiguration and the decision-making quality within organizations. When the employees have strong learning capabilities, they will be able to understand the data and extract insights such as descriptive, integrative, and reconfiguration, which can ultimately enhance the quality of the decisions made thereafter. The integration capabilities can harness the power of collaborating with internal and external information sources to acquire the information needed and refine the data insights.

Likewise, by possessing re-configuration capabilities, the organization will adapt and swiftly change the internal orientation to match the changing external environments by pursuing the directions raised by the data insights. Such mediating integration of data insights with dynamic capabilities and decision-making facilitates the effectiveness and efficiency of decisions. Therefore, it is hypothesized that;

H6. Data-driven insights are significantly and positively mediating the relationship between Learning Capabilities and Decision-making effectiveness
H7. Data-driven insights are significantly and positively mediating the relationship between Learning Capabilities and Decision-making efficiency
H8. Data-driven insights are significantly and positively mediating the relationship between Integration Capabilities and Decision-making effectiveness
H9. Data-driven insights are significantly and positively mediating the relationship between Integration Capabilities and Decision-making efficiency
H10. Data-driven insights are significantly and positively mediating the relationship between Reconfiguration Capabilities and Decision-making effectiveness
H11. Data-driven insights are significantly and positively mediating the relationship between Reconfiguration Capabilities and Decision-making efficiency

METHODS

Research Design

The current study employed a quantitative research design for exploring the relationship between the dynamic capabilities of learning, integration, and re-configuration and the decision-making quality. Further, the mediating role of data-driven insights was also examined. The theoretical lens was set with the dynamic capabilities theory to explain the relationship between the variables of the study.

Target Population and Sample

The study population comprised top management and executive-level employees engaged in big data activities and dynamic capabilities from the hospitality sector of Pakistan. Chief Executive Officers, General Managers, and Assistant Executive Managers from 3-star, 4-star, and 5-star hotels were approached for data collection. The decision to concentrate on these hotel categories is due to their greater capacity for big data activities, both financially and non-financially (Gupta & George, 2016; Wamba et al., 2017). The multistage sampling method was employed with cluster sampling and simple random sampling respectively.

The clusters were identified as 3-star, 4-star, and 5-star hotels in the seven administrative regions of the country: Punjab, Sindh, Baluchistan, Khyber Pakhtunkhwa, Gilgit Baltistan, Kashmir, and the Federal area. These hotels were screened for big data usage in their decision-making. Simple random sampling was then applied to generate the final sample, ensuring each hotel had an equal chance of selection reducing researcher bias to enhance the generalizability of results (Hair et al., 2010b). The population was identified as 599 hotels (3-star, 4-star, and 5-star) using big data and dynamic capabilities based on which a sample of 217 hotels was selected using Krejcie and Morgan's (1970) table. To counter potential low response rates, 499 questionnaires were distributed, seeking one response per hotel at the firm level.

SMEASURE

A survey was conducted using a structured questionnaire divided into 2 sections. Section A consisted of questions seeking demographic information of the respondents and the initial filtering questions to ensure the hotels have been using big data for a significant time. Section B contains questions measuring the variables of the study adopted from established prior studies. Dynamic capabilities were analyzed against an adapted scale containing 12 items measuring responses for dynamic learning, integration, and re-configuration capabilities(Lin & Wu, 2014). Data-driven insights were measured on 11 items as suggested by (Ghasemaghaei & Calic, 2019). Moreover, the decision-making quality was measured on 4 items for each dimension i.e., efficiency (Shamim et al., 2019) and effectiveness (Visinescu et al., 2017) of decision-making.

Data Collection Procedure

The data collection process started with the initial screening of the hotels for their use of big data and dynamic capabilities. Approval for participation in the survey was sought from the administration of the selected hotels. A pilot study was conducted on 20 respondents from hotels and academic experts in the domain. Minute changes were made in the flow of questions following the suggestions. The questionnaires were distributed to the top-management executives such that one response for each hotel is received. Further to reduce the chances of common method bias the questionnaires were divided into different sections and time lapses were utilized to reduce common method bias in the responses.

Data Processing and Analysis

The data processing and analysis were conducted by performing descriptive and inferential statistical analyses using SPSS 26 and Smart PLS 4.0. A confirmatory factor analysis was conducted to establish the validity and reliability of the scale. Further, the Partial Least Squares Structural Equation Modeling (PLS-SEM) was performed for measurement and structural model assessment. Initial screening of the data for missing values and outliers involved replacing missing values with mean values, and outliers were identified using the Mahalanobis distance formula.

Findings

The findings of the investigation are derived from (a) a Partial Least Square (PLS) algorithm and (2) a bootstrapping technique. The PLS algorithm was employed to ensure both convergent and discriminant validity of the measurement model. Secondly, bootstrapping was applied to generate a structural model assessment. This method involves repeatedly sampling the data to estimate the accuracy and stability of the model's parameters, providing a robust evaluation of the structural relationships

Measurement Model Assessment

A measurement model assessment is crucial for verifying that the constructs are accurately measured and distinct from each other to ensure convergent validity and discriminant validity. Convergent validity explains that the items measuring a construct consistently measure the same underlying concept. It was analyzed using three key indicators: Average Variance Extracted (AVE), Composite Reliability (CR), and factor loadings. The AVE evaluates that the items collectively explain a significant portion of the construct's variance. Composite Reliability shows the internal consistency of the items indicating the reliability of the construct. Factor loadings explain the correlation between each item and the construct to confirm that it is a strong indicator of the concept being measured. These metrics provide a comprehensive evaluation of convergent validity, ensuring that the items are both reliable and accurately reflective of the construct. The factor loadings as shown in Table 1 are all above the threshold value i.e., 0.6 indicating that the items are strong indicators of the concept measured. The Cronbach's alpha values for the constructs are satisfactorily above the threshold value of 0.7 and lie between ranges of 0.898 to 0.937. The composite reliability values are safely above the threshold value of 0.7 and range 0.93 to 0.96. Likewise, the AVE of all constructs ranged 0.718 to 0.85 which is much above 0.5 i.e., the recommended value. Cronbach alpha is above 0.70 which indicates the acceptable internal consistency of the items measuring the construct (Hair et al., 2017). Secondly, the discriminant validity assessment was confirmed using the heterotrait-monotrait ratio of correlation (Henseler et al., 2015). As shown in Table 2 all values are below the recommended 0.9 value establishing the discrimination validity and confirming the items measuring various constructs are distinct. Refer to Figure 2, Table 1, and Table 2.

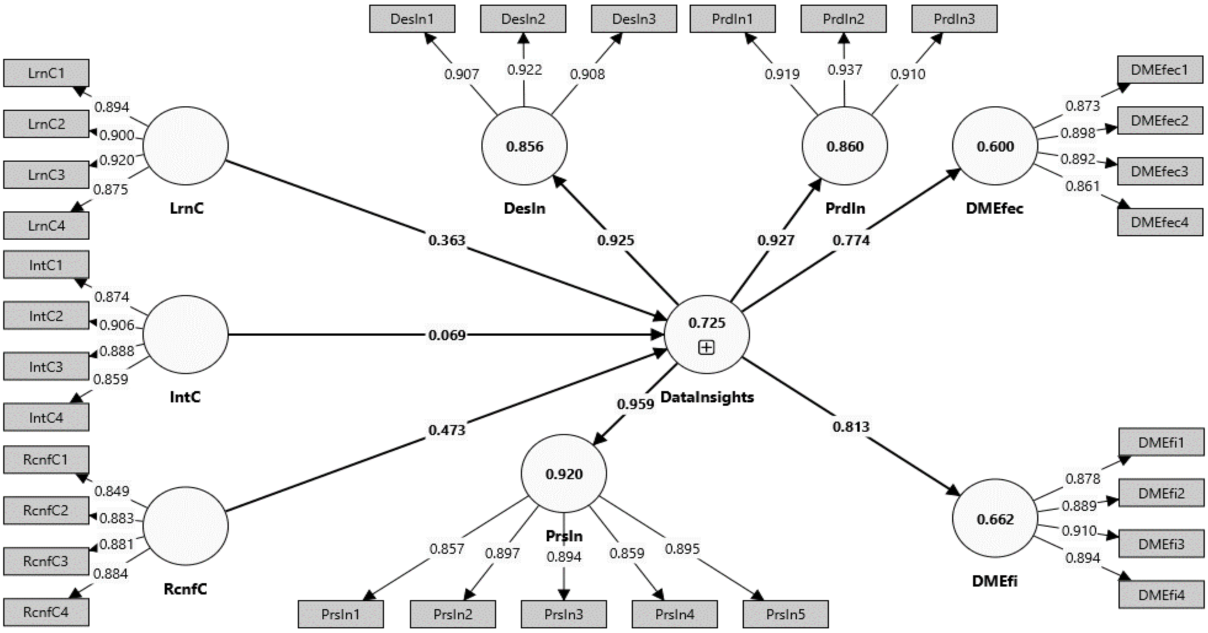

Figure 2.
Measurement Model Assessment – Convergent and Discriminant Validity

Table 1.
Convergent Validity

First Order Constructs	Higher Order Constructs	Items	Loadings	Cronbach's Alpha	CR	AVE
Learning Capabilities				0.919	0.943	0.805
		LrnC1	0.895			
		LrnC2	0.901			
		LrnC3	0.92			
		LrnC4	0.874			
Integrating Capabilities				0.905	0.933	0.778
		IntC1	0.875			
		IntC2	0.907			
		IntC3	0.89			
		IntC4	0.855			

Reconfiguration Capabilities				0.898	0.929	0.765
		RcnfC1	0.855			
		RcnfC2	0.889			
		RcnfC3	0.881			
		RcnfC4	0.873			
Descriptive Insights				0.899	0.937	0.832
		DesIn1	0.907			
		DesIn2	0.922			
		DesIn3	0.908			
Predictive Insights				0.911	0.944	0.85
		PrdIn1	0.919			
		PrdIn2	0.937			
		PrdIn3	0.91			
Prescriptive Insights				0.927	0.945	0.775
		PrsIn1	0.857			
		PrsIn2	0.897			
		PrsIn3	0.894			
		PrsIn4	0.859			
		PrsIn5	0.895			
	Data Driven Insights			0.961	0.956	0.718
		DesIn1	0.861			
		DesIn2	0.829			
		DesIn3	0.841			
		PrdIn1	0.86			
		PrdIn2	0.85			
		PrdIn3	0.853			
		PrsIn1	0.849			
		PrsIn2	0.842			
		PrsIn3	0.843			
		PrsIn4	0.82			
		PrsIn5	0.867			
Decision Making Effectiveness				0.904	0.933	0.777
		DMEfec1	0.871			
		DMEfec2	0.902			
		DMEfec3	0.893			
		DMEfec4	0.858			
Decision Making Efficiency				0.915	0.94	0.798
		DMEfi1	0.878			
		DMEfi2	0.891			
		DMEfi3	0.912			
		DMEfi4	0.89			

CR Composite Reliability , AVE Average variance extracted

Table 2.
Discriminant Validity

	DMEfec	DMEfi	DataInsights	IntC	LrnC	RcnfC
DMEfec						
DMEfi	0.85					
DataInsights	0.829	0.865				
IntC	0.79	0.86	0.812			
LrnC	0.824	0.814	0.841	0.894		
RcnfC	0.818	0.872	0.872	0.822	0.863	

DMEfec=decision-making effectiveness, DMEfi=decision-making efficiency, IntC=integration capabilities, LrnC=learning capabilities, RcnfC=reconfiguration capabilities

STRUCTURAL MODEL ASSESSMENT

The structural model assessment was performed by using bootstrapping to assess the relationship between the constructs of the study and test the hypotheses. Bootstrapping is a re-sampling technique that allows robust statistical inferences for hypotheses testing by calculating and comparing key statistical indicators i.e., beta values, t-statistics, and p-values (Hair Jr et al., 2014). The results for direct and indirect relationships are detailed in Table 3, Table 4, and Figure 3. The analysis indicates that the direct relationships between the learning capabilities and data insights ($\beta = 0.362$; $t = 6.717$) and re-configuration capabilities and data-driven insights ($\beta = 0.474$; $t = 7.671$) are positive and significant. However, the relationship between the integration capabilities and data-driven insights was not supported statistically ($\beta = 0.068$; $t = 1.16$). The hypotheses are supported based on the critical value ($t>1.645$; $p<0.05$). Further, the positive influence of data-driven insights is established with decision-making effectiveness ($\beta = 0.775$; $t = 33.737$) and decision-making efficiency ($\beta = 0.813$; $t = 39.792$).

In addition to the direct hypotheses results, the indirect relationships mediated by the data-driven insights between the learning capabilities with decision-making effectiveness (H6) and efficiency (H7) are positively and significantly established such that ($\beta = 0.281$; $t = 6.581$) and ($\beta = 0.295$; $t = 6.719$) respectively. Likewise, the re-configuration capabilities facilitated by data insights positively reinforce the decision-making effectiveness (H10: $\beta = 0.367$; $t = 7.509$), and efficiency (H11: $\beta = 0.386$; $t = 7.483$). Contrarily, the integration capabilities did not establish a statistically significant relationship with decision-making effectiveness (H8: $\beta = 0.053$; $t = 1.155$) and efficiency (H9: $\beta = 0.048$; $t = 1.154$) even when mediated by the data insights.

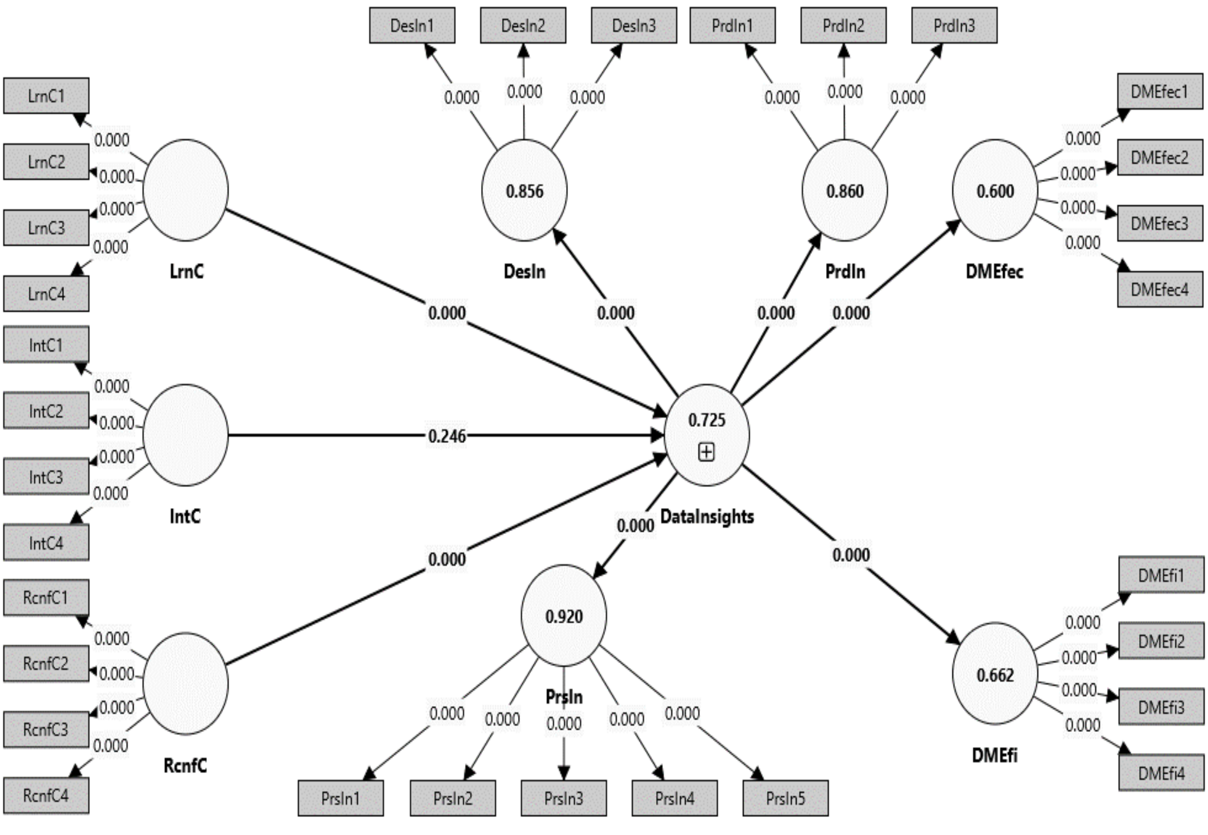

Figure 3.
Structural Model Assessment

Table 3.
Hypothesis testing – Direct Relations

Hypotheses	Relationship	Beta	S.D.	t-value	P values	L.L.	U.L.	Decision
H1	LrnC -> DataInsights	0.362	0.054	6.717	0	0.254	0.466	Supported
H2	IntC -> DataInsights	0.068	0.059	1.16	0.246	-0.049	0.184	Not Supported
H3	RcnfC -> DataInsights	0.474	0.062	7.671	0	0.351	0.595	Supported
H4	DataInsights -> DMEfec	0.775	0.023	33.737	0	0.726	0.816	Supported
H5	DataInsights -> DMEfi	0.813	0.02	39.792	0	0.768	0.848	Supported

LL= lower limit , UL= upper limit , S.D= standard deviation

Table 4.
Hypothesis testing – Indirect Relations

Hypotheses	Relationships	Beta	S.D.	t-value	P-value	L.L.	U.L.	Decision
H6	LrnC -> DataInsights -> DMEfec	0.281	0.043	6.581	0	0.196	0.362	Supported
H7	LrnC -> DataInsights -> DMEfi	0.295	0.044	6.719	0	0.206	0.376	Supported
H8	IntC -> DataInsights -> DMEfec	0.053	0.046	1.155	0.248	-0.037	0.143	Not Supported
H9	IntC -> DataInsights -> DMEfi	0.056	0.048	1.154	0.248	-0.039	0.15	Not Supported
H10	RcnfC -> DataInsights -> DMEfec	0.367	0.049	7.509	0	0.268	0.459	Supported
H11	RcnfC -> DataInsights -> DMEfi	0.386	0.051	7.483	0	0.283	0.486	Supported

LL= lower limit, UL= upper limit, S. D= standard deviation

DISCUSSION

The study offers novel observations by investigating the individual effects of learning, integration, and re-configuration capabilities independent of each other on generating data-driven insights and decision-making quality. Prior literature has shown a relationship between various bundles of capabilities such as analytical capabilities and dynamic capabilities in information systems on various organizational outcomes(Mikalef et al., 2020; Steininger et al., 2022). The study strengthens the role of dynamic capabilities in generating data-driven insights and decision-making quality which is vital to identify which capability to invest in more. The study's findings indicate a positive and significant relationship between learning capabilities and data-driven insights highlighting that continuous learning is essential in enhancing the ability to derive valuable data insights. The learning process involves knowledge creation by setting up training sessions for cross-departmental teams according to the needs of the organization. Such extensive learning, therefore, enhances the ability to generate rich data insights such as descriptive, predictive and prescriptive.

The result is consistent with prior studies indicating the positive influence of dynamic capabilities on data insights (Gupta et al., 2020). Similarly, results indicate that re-configuration capabilities have a strong positive impact on data-driven insights, accentuating the role of adaptability and flexibility in leveraging data for strategic advantages. Organizations maintain clear and efficient communication with partner organizations which enhances their ability to generate data insights and lead to attain the abilities to swiftly respond to market changes. Literature supports the role of reconfiguration capabilities on influencing organizational outcomes (Khan et al., 2021). The current study accentuates the role of reconfiguration capabilities on the decision-making quality as well. Integration capabilities are an essential aspect involving the ability to gather and analyze customer, market, and industry-specific information which could be vital for the enhanced organizational outcomes (Deng & Noorliza, 2023). However, the relationship between the integration capabilities and the data insights was not statistically established. An explanation of this can be that integration capabilities alone independent of other capabilities such as learning, and re-configuration capabilities could not generate a positive influence on the data insights.

Moreover, data-driven insights were found to cast a significantly positive influence on both decision-making effectiveness and efficiency, indicating the importance of successfully harnessing the data insights in making more informed and timely decisions(Sarker, 2021). The research outcome is in congruence with the prior literature on supporting the critical role of data in improving organizational decision-making processes. The mediating role of data-driven insights between learning capabilities, reconfiguration capabilities and decision-making outcomes is established through statistical analysis. The mediating role of data-driven insights is in support of the prior literature (Awan et al., 2021; Ghasemaghaei & Calic, 2019). Both the learning capabilities and the reconfiguration capabilities enhance decision-making quality by positively affecting the effectiveness and efficiency facilitated by valuable data-driven insights. The re-configuration capabilities positive reinforcing effect suggests the influence of decision-making outcomes via data-driven insights, reinforcing the notion that adaptability in processes and strategies is crucial for effective and efficient decision-making.

Contrary to expectations, the statistical results did not indicate a significant link between the integration capabilities and data-driven insights. Moreover, the indirect relationship between the integration capabilities and the decision-making quality through the data insights was not statistically established. This finding suggests that simply integrating data sources and systems may not be sufficient to generate valuable insights or improve decision-making processes. It underscores the need for more nuanced approaches to integration that go beyond mere data consolidation, focusing instead on how data is utilized and interpreted within the organizational context.

THEORETICAL IMPLICATIONS

The study offers a novel contribution to the literature by providing empirical evidence supporting the role of learning and reconfiguration capabilities in promoting quality decision-making. The mediating role of data-driven insights between the dynamic capabilities and decision-making outcomes has been investigated to unravel the complex interplay between dynamic capabilities such as learning, integration, and re-configuration and their impact on the decision-making quality. Several important theoretical implications can be extracted from the current investigation as limited literature is available on dynamic capabilities with particular reference to the decision-making quality. Dynamic capabilities i.e., a combination of learning, integration and re-configuration capabilities have been investigated for their individualized effect on the generation of data insights and decision-making quality. Differentiating the roles of dynamic capabilities into its parts such as learning, integration, and reconfiguration capabilities, has extended the contributions to the literature on dynamic capabilities. This leads to important findings of the study about the non-supportive effect of integration capabilities on data insights and decision-making quality which has opened doors for further investigation. This insight suggests that the role of integration capabilities in isolation may be over-emphasized in literature. Integration capabilities in isolation cannot generate a positive influence but may require the support of other capabilities. Moreover, the study has extended the literature on data-driven insights by examining its mediating role between dynamic capabilities and decision-making effectiveness and efficiency. The positive role of data-driven insights ensures that actionable insights are required to translate the impact of dynamic capabilities which in turn enhance decision-making quality.

PRACTICAL IMPLICATIONS

From the practical viewpoint, the findings provide rich guidance for organizations focusing on improving their data-driven decision-making quality. It is vital to ensure that learning and reconfiguration capabilities are nurtured to enhance data-driven insights and improve decision-making outcomes. The capabilities of learning and re-configuring involve the dynamic application of sharing, training, flexibility and adaptability across all departments and hierarchical levels of the organization. Organizations should prioritize and invest more in developing learning capabilities by providing cross-departmental training. The constant and consistent focus on professional development will enhance learning capabilities across the organization leading to the ability to generate valuable data insights supporting the decision-making.

Further, organizations operating in dynamic environments must be capable of responding to market changes swiftly. This agility and responsiveness are developed when the re-configuration capabilities are strong enough to respond to the predictive and prescriptive data insights. Re-configuration capabilities such as reallocation of resources, restructuring of teams and units, and re-strategizing to respond to dynamic changes will harness the organization's ability to leverage data insights for better decision-making outcomes. A surprising revelation of the study identified that integration of organizations' data and information sources is necessary however alone it cannot produce data insights. Therefore, organizations must ensure that robust learning and reconfiguration capabilities are developed to derive value from the integrated data sources. The pivotal role of data-driven insights has been established through this investigation; therefore, organizations should systematically incorporate data insights such as descriptive, prescriptive, and predictive insights into their decision-making processes to improve the quality of decisions. The implementation of decision support dashboards offering actionable and impactful real-time data insights to decision-makers can ensure quality decision-making. These practical strategies can better harness the dynamic capabilities of learning, integration, and re-configuration to achieve improvement in decision-making organizations.

LIMITATIONS AND FUTURE RESEARCH

The current study did not consider any contextual explanation of the phenomenon, future investigations can examine the theoretical model for different contextual factors by considering factors like industry-specific characteristics, organizational culture, and environmental dynamism to provide a comprehensive understanding. The study employs a cross-sectional design therefore to improve causality and generalizability, a longitudinal study is suggested to uncover the associations between dynamic capabilities and the decision-making quality mediated by the data insights.

The unexpected finding about the non-supportive role of integration capabilities opens doors for further investigation. Further investigations could analyze the favourable conditions for the integration capabilities to produce a positive influence on data insights and decision-making. Additionally, the role of potential mediators and moderators could be examined strengthening the theoretical framework.

CONCLUSION

This paper therefore adds to the literature an underpinning of complex relationships among various organizational capabilities as they bear on decision-making, further illuminated by data-driven insights. In particular, the results underline learning and reconfiguration capabilities as two important empowerment factors of decision-making by data, but also their limitation by integration capabilities. Such insights offer useful guidance to practitioners and researchers who are striving to enhance the effectiveness and efficiency of organizational decision-making through strategic usage of data.

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