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Explorative Learning as a Pathway Linking Big Data Analytics Enabled Dynamic Capabilities to Organizational Decision Making

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ABSTRACT

The recent Big Data Analytics (BDA) has also revolutionised the way organisations derive intelligence and react to environmental dynamics. The proposed study of this research suggests the design of a study by utilising the "Dynamic Capabilities" View and the Organisational Learning Theory as the means of identifying the interdependence between Big Data Analytics-enabled Dynamic Capabilities (BDAEDC) and Decision-Making Quality of Organisations (DMQO),through Explorative Learning (ELR). The survey was conducted using a structured questionnaire, which was administered to managers of various organisations. The proposed model was tested using "Partial Least Squares Structural Equation Modelling" (PLS-SEM). The results indicate that BDAEDC has a significant positive effect on decision quality and exploratory learning. Moreover, exploratory learning has a substantial influence on the quality of the decision-making process, which proves its significance in prompting necessary changes for organisations to adopt, innovate, and improve the quality of strategic decisions. The mediation analysis suggests a partial mediating effect of exploratory learning in the relationship between BDAEDC and DMQ, thereby reinforcing the idea that the value of data-enabling capabilities can be delivered not only directly but also indirectly, through facilitated learning within the organization. The article has helped provide a theoretical explanation of the interaction between dynamic capabilities, big data, and knowledge, while also offering practical advice to managers and coordinating the alignment of BDA initiatives and learning-based practices to enhance the quality of decision-making.

Introduction

A rapid rate of technological change, stiff competition, and further uncertainty characterize the current business landscape. It is under this observation that organisations constantly face pressure to evolve to survive and expand, and thus, they require adjustments in their operations, practices,and structure. “Big Data Analytics” (BDA) has been considered as one of the most disruptive capabilities in the current digital world (Reference required). It is essentially transforming the way companies generate knowledge and make decisions. BDA has the potential to assist organisations in developing trend reports and isolating trends that would not have been previously identified. BDA outputs that would result in optimal efficiency and effectiveness through the processing of large volumes of structured and unstructured information and data (Constantiou & Kallinikos, 2015; Naresh & Suneetha, 2016). The global BDA market, which was expected to reach “USD 307.51 billion in 2023 and is projected to exceed USD 924.39 billion by 2032”, is a testament to the rapid increase in reliance on analytics both as a strategy and an operational tool (Juchinson, 2017).

Organisations require additional organisational mechanisms to present the BDA investments in action effectively (Sultan et al., 2024). The “Dynamic Capabilities View” (DCV) is a robust theoretcal framework that can be used to explain how firms can turn technological resources into strategic assets. Teece and Pisano (1997) proposed the concept of dynamic capabilities as the firm's ability to integrate, invent, and restructure both external and internal competencies in response to the dynamic nature of the environment. Teece (2007) also elaborates on three key elements of dynamic capabilities: sensing opportunities, committing resources to seize opportunities, and reconfiguring assets to stay competitive. In a data-rich context, it is the amplification of those processes as Dynamic Capabilities (BDAEDC) that assures organisations change, taking the form of feeling predictive insights and seizing opportunities by aligning resources to the emerging demands of the market, and lastly, the processes of continuous adaptation (Mikalef et al., 2020).BDAEDC is thus a valuable facilitator of agility, innovation, and responsiveness.

Despite the acknowledged potential of BDAEDC, scholars have reported that there is little evidence in practice of the model's impact on “organisational performance" that is practical and well-connected to each other (Bahrami, 2022). The quality of decision-making (DMQO) caused by BDAEDC is not fully determined (Elragal & Elgendy, 2024). The quality of the decision made refers to the extent of practical and efficient choices within an organisation, in terms of the goodness of the decision and the resources expended in its attainment (Clark et al., 2007; Kaltoft et al., 2014).High-quality decisions determine high performance, reduce risks, and ensure long-term sustainability. Past researchers have noted that BDA with dynamic capabilities can facilitate the making of timely, more accurate, and strategic decisions (Seddon et al., 2017; Janssen et al.,2017). Although the avenues of BDAEDC's influence on DMQO remain understudied, the gap in understanding how firms can utilize their technological capabilities to make superior managerial and organizational choices is substantial (MMikalef et al., 2020; Haider et al., 2024; Yoshikuni et al.,2025).

Interestingly, there was potential for exploring organisational learning, specifically exploratory learning. Explorative learning relies on experimentation with new knowledge and adopting new ways in uncertain situations (March, 1991). Unlike exploitative learning, which focuses on process and efficiency gains, exploratory learning enhances innovation and flexibility, enabling organisations to identify opportunities in their operations and markets. It has been demonstrated that exploratory learning can positively impact decision-making processes by increasing the knowledge base, providing the ability to think creatively, and empowering organisations to make improved and informed decisions (Helfat & Raubitschek, 2000; Visinescu et al., 2017). BDAEDC can be a source of explorative learning, in the sense that BDAEDC will allow firms to gain access to new sources of insights and information. Through analytics-oriented skills, organisations are likely to prepare themselves to venture, create, and modify plans in a rapidly changing environment, which eventually enhances the quality of their decisions (Ferreira et al., 2020).

Although earlier studies have provided insights into the importance of BDA and learning processes, they still lack a comprehensive understanding of the level at which extant BDAEDC facilitates exploratory learning behavior and its influence on the quality of decision-making. The general growth that comes along with BDA or dynamic capability, in general, has already been valued as a significant one in the literature without necessarily defining the moderating role of learning in the process (Pezeshkan et al., 2016; Mikalef et al., 2020). Subsequently, the post-fact impression of the activities that could be undertaken by data-facilitated capabilities to inform an organisational decision successfully would reveal a knowledge gap.

To fill this gap, the proposed study will examine how the ability of BDA-enabled dynamic capabilities can influence the quality of decisions made, primarily by exploring the role of exploratory learning as a mediator. The paper can contribute to both of these sources, primarily because it synthesizes ideas from the Theory, specifically the "Dynamic Capabilities View". It has demonstrated how data-enabled capabilities do not limit themselves to the technology infrastructure, but rather tap into the learning process within the organisation and contribute to effective decision-making. Meanwhile, it also provides some practical tips to managers, highlighting the essence of developing exploratory learning as an addition to effective big data analytics operations. Through this study, the researcher will gain insight into how companies can leverage the potential of the big data they are investing in, creating dynamic capabilities that not only foster agility and innovation but also enable more effective and efficient decisions within a complex and uncertain business environment.

Review of the Literature and Hypothesis

Big data-enabled dynamic capabilities

The ability of an organisation to scan the enormous volume of data, gain knowledge about the opportunities and threats, and be able to arrange the resources so they can be used effectively to respond is known as BDA-enabled dynamic capabilities (DCs). Through this process, companies align their internal learning with external requirements. The position of BDA-enabled DCs is now a heavy burden on management studies (Wamba, 2017). Ordinary and dynamic capabilities are contrasted in the literature (Winter, 2003). The resource base of a firm is commonly called ordinary capabilities (Pezeshkan et al., 2016). They are included in the practices that improve the efficiency level in operation, management, and governance practices (Teece, 2014).

Later, dynamic capabilities were coined as dynamic capabilities or higher-order capabilities (Teece, 2014) as a variant of the "resource-based view (RBV) to explain competitive advantage in turbulent environments" (Winter, 2003; Teece, 2014). The definition of organisation-level capabilities provides that organisations can interweave, build, and reconfigure both internal and external capabilities to meet, and probably affect, swiftly shifting business worlds (Teece, 2014,p. 1395). These are all desired features that businesses strive to achieve (Schreyog & Kliesch-Eberl, 2007), and it is a valuable addition to these qualities to be able to operate big data analytics.

The various concepts of DCs in management literature differ considerably. According to Teece (2014), three components are set up: "sensing, seizing, and reconfiguring. Sensing is about identifying and measuring" emerging technologies and market needs. Seizing entails allocating resources to capitalise on opportunities and generate value. Reconfiguring entails reorganizing the firm's resource base to capitalise on new opportunities. To support their position, Wilhelm et al.(2015) mention that DCs sense, learn, and reconfigure and state that learning is similar to seizing, according to Teece, which is the capacity of the firm to create the means and tools to respond to the changes and opportunities of the environment in the most efficient manner (p.329).

Dynamic Capabilities View (DCV)

The "Dynamic Capabilities View (DCV) is a robust theoretical framework that offers a holistic description of how firms can model their changing environment and emerge victorious". DCV argues that, in addition to possessing valuable resources, firms must also develop the capacity to restructure these resources in response to environmental changes (Teece & Pisano, 1997). Teece (2007) would go an extra mile in developing the framework and would propose three micro-foundations of "dynamic capabilities: Sensing: the ability to identify opportunities and threats. Seizing: the power to harness resources to add value to capture. Reconfiguring: the potential of recalibrating or redefining the organisational resources".

These dynamic capabilities have been significantly improved in terms of BDA. BDA technologies also offer real-time feedback and predictive analytics, enabling firms to gain a deeper understanding of market trends, capitalise on new opportunities, and make informed, real-time adjustments to resources and strategies. As an illustration, real-time analytics enable marketing managers to make adjustments to campaigns in real-time, allowing them to make more informed forecasts and manage risks more efficiently with the assistance of predictive models. BDA thus enhances the three dynamic capabilities and aligns organizational learning with environmental pressures. These capabilities are particularly applicable in high-speed settings, where businesses must not only survive but also exploit first-mover benefits.

BDA-enabled DCs and Decision-making Quality of an Organization

The effectiveness and efficiency of the decision-making process are evaluated in this paper, which is consistent with the earlier works of the same type (Clark et al., 2007). In the modern world of DCs supported by the power of big data analytics, companies are in search of the most efficient means to implement the latter (Visinescu et al., 2017). This would improve the quality of decisions, especially with the introduction of managerial experience, business intelligence tools, and these capabilities (Seddon et al., 2017). The aspect that can be regarded as the quality of decision-making or decision-making effectiveness is the satisfaction of the decision-maker with the intended outcomes of the decision-making process (Kaltoft et al., 2014). On the other hand, decision-making efficiency takes into consideration the resources that will be utilized in the process, such as time and cost. Business intelligence can be facilitated through the use of big data management, enabling decision-makers to utilize data, information, and knowledge to address problems and make informed decisions at both the individual and organizational levels (Clark et a1.,2007;Visinescu et al., 2017).

Dynamic capabilities encompass sensing, seizing, and reconfiguring processes that can be crucial in enhancing the quality of decisions made within an organization (Teece, 2007). Firstly, sensing entails a company's ability to detect, understand, and evaluate emerging technologies in relation to previous customer demands, and respond to business failures. Second, seizing entails the firm's capability to expand its required facilities to meet customer needs, seize business opportunities, and utilize business value. Lastly, reconfiguring the current base of resources, which can be supplemented by new sources, in order to capitalize on opportunities within the organization. All these abilities will help the organization acquire in-depth knowledge regarding decision-making and the way to enhance its quality.

The Theory of dynamic capabilities (DCs) considers the potential of long-term companies to renew and create new capabilities that guarantee them a long-term competitive edge (Teece, 2007; Linden & Teece, 2018). The effectiveness of a specific firm depends on the accuracy of decisions made by an organizational brain that can be supported by Dynamic Capabilities, facilitated by big data analytics. This is because the high-quality decision-making that is facilitated by big data analytics and Dynamic Capabilities (DCs) is directly associated with high performance and efficiency. These also help a firm make sound choices based on accurate information. As a result, the capability of the company to make decisions supported by the utilization of big data analyticS-enabled DCs can potentially lead to a profound change in the quality of the decision-making process, which the available literature sources can also corroborate (Chen et al., 2016).

Additionally, Pezeshkan et al. (2016) have demnonstrated that the quality of decision-making is a result of the effectiveness and efficiency of decision-making, indicating that both exploitative learning and exploratory learning can be employed in the study of decision-making quality.

As Teece (2007) notes, such abilities are termed dynamic capabilities, which require high demand to be restructured in order to enable evolutionary fitness, remove unwanted path dependencies, and achieve efficiency. On the same note, Wamba et al. (2017) value multi-dimensional capabilities of big data analytics as a game changer because they have a high level of operational and strategic capabilities that render them disruptive in their generation in terms of efficiency and effectiveness. Furthermore, Yiu (2012) believes that the DCs utilizing big data analytics can enhance the quality of the decisions made by them and, therefore, become more effective and efficient.

H1:The BDA-enabled DCs positively influence the decision-making quality of the organization

BDA-enabled DCs and explorative Learning

BDA-supported Dynamic Capabilities enable the firm to identify learning opportunities and understand what is expected in a highly dynamic business environment, ultimately leading to the firm's survival and prosperity (Mikalef & Pateli, 2017). The other advantages that a company would realize in BDA-empowered DCs include the development of exploratory learning to optimize business expenditures, organizational-level change, and efficient decision-making (Pezeshkan et al., 2016). Thus, DCs that are based on BDA (BDA-enabled DCs) ought to be capable of creating a competitive advantage. According to Martin (2000), these capabilities are necessary to leverage existing strengths and convert them into new ones, ultimately achieving a competitive advantage. This is important because having just possession of resources is not enough. However, no company can generate long-term advantages in its resources without knowing how to utilize them effectively (Teece, 2007).

Besides, Dynamic Capabilities (DCs) facilitate the firms to improve their learning and adaptation abilities through new (exploratory learning), and thus lead to better decision making in firms. In particular, DCs facilitated by Big Data Analytics enable businesses to adjust their strategies, refining existing ones and developing new ones. This assists in maintaining competitive advantages in the firms as well as making better decisions. Using simple terminology, a company registering high BDA-enabled DCs will have an improved chance of enhancing learning in both new and familiar contexts. As a result, it has a positive impact on exploratory learning in BDA-enabled DCs.

H2:The BDA-enabled DCs positively impact Explorative Learning.

Explorative learning and decision-making quality of the organization

It is a process that entails seeking novelty in knowledge, ideas, and innovation, which is a form of exploratory learning. It promotes new ideas and encourages exploration of new things. Exploratory learning can also lead to higher-quality decision-making, revealing new meanings and opportunities for informed choices. March (1991) revised the notion that the same exploratory learning also helps organizations adjust to new environments and make more adaptive decisions. The quality of the decision made is also a direct outcome of exploratory learning, as it provides the organization with the opportunity to explore new spheres of knowledge and competence, and ultimately enrich them. Helfat and Raubitschek suggest that exploration learning can result in the attractiveness of highly valuable resources and capabilities that are discovered by the exploration (Helfat & Raubitschek, 2000). Such a conclusion can then be applied in order to enhance the quality of strategic decisions. These two learning processes have played a crucial role in the contemporary business environment, where organizations are expected to thrive in a dynamic and competitive landscape. Organizations become receptive to various strategic choices since they create new prospective capabilities to be cultivated, thereby creating opportunities to make not only pragmatic but also creative decisions (Visinescu et al., 2017). The latter type of learning enables firms to take calculated risks, whereby the possibility of breakthroughs, whether in products, procedures, or services, is high. Using the example of new technologies or business models created through exploratory learning can make significant contributions to an organisation's performance (Ferreira et al., 2020).

Exploratory learning within companies is essential for improving decision-making. It also enhances innovativeness, flexibility, and the learning process, which are crucial in the modern business environment, where everything is deemed to be moving at a breakneck pace (Visinescu et al., 2017). Organisations can make more innovative, creative, strategic, and successful decisions through a culture of exploration. Exploratory learning also makes firms more dynamic and responsive, thereby enabling them to thrive and ultimately succeed in a highly competitive global marketplace. The downside is that, not knowing where to go, you are not sure where you will end up. The trade-off between exploitative learning and exploratory learning enables organisations to strike a balance between current operations and exploring new sources of growth. (e.g., Clauss et al., 2021).

H3: Exploratory learning positively affects the quality of thinking in decision-making by the organisation.

Mediation Role of Exploratory Learning

The exploratory learning process is a “significant mediator of both the dynamic capabilities of big data and the quality of decision-making”. Exploration is one of the most significant aspects of it, entailing going out of frame of reference (Zollo & Winter, 2002). The process of discovering new knowledge in large amounts of data is exploration, which is used to utilize the dynamic capabilities that big data provides. Unlike exploitative learning, where all issues revolve around ongoing processes, explorative learning compels organisations to pursue new knowledge, experiment, and even test new ways (March 1991: 85). This allows firms to obtain novel knowledge of BDA,which guarantees a flexible and strategic novelty.BD-operating DC capabilities help organisations access and analyse the most up-to-date tools. However, through exploratory learning, these skills are applied in order to learn new things and be innovative.

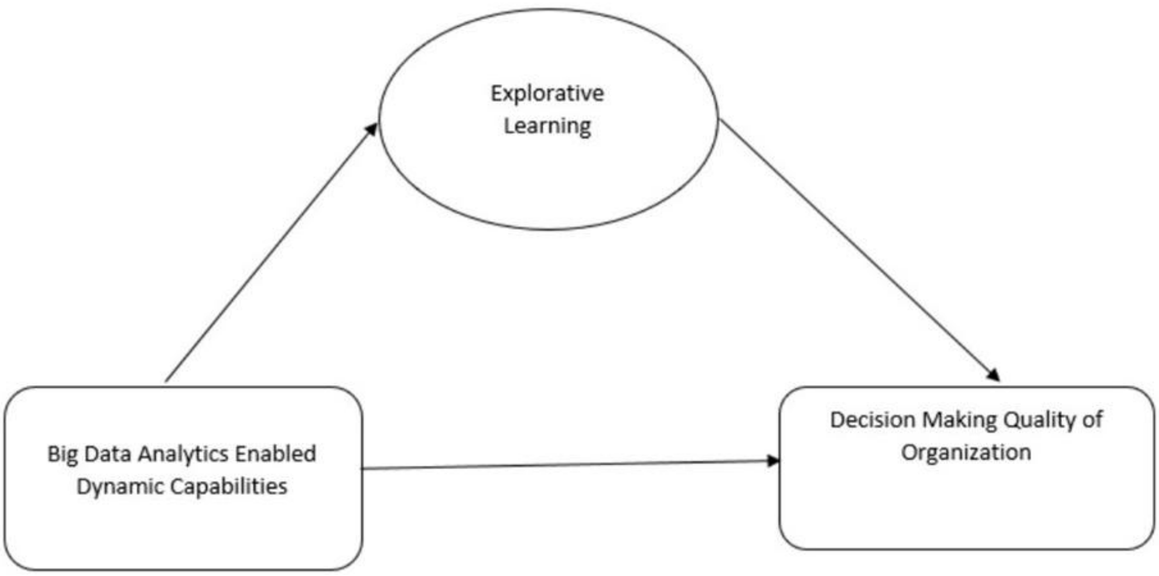
Exploratory learning enhances the effectiveness of decision-making as a mediator, enabling organisations to identify new opportunities and develop innovative solutions. BDA is one of the experiences that enables an organisation to respond quickly to changing realities, as it can recognise new trends and alter its strategy in response to them. According to March (1991), ventureous learning is a mandatory learning in an organisation operating within an ever-changing market because it enables such an organisation to make adaptive and innovative decisions that are suited to enhancing its competitiveness in the long term.

Exploratory learning also helps companies broaden their horizons in decision-making, leading to the development of newv products, services, and strategies. The institutions that implement the exploratory learning are better positioned to receive the advantages associated with BDA, i., they are ready to explore new lands and experiment (Caniels et al.,2017). Such flexibility has enable more effective decision-making in response to changes and the utilisation of data as a strategic resource, as firms become more responsive to changes (Rialti et al., 2018).

Additionally, through the aid of exploratory learning, the organisations can substantially enhance their absorptive capacity, which is one of the factors of the internalisation of external knowledge in the decision-making process (Chen et al., 2016). This enables companies to collect, process, and uniquely utilize information, thereby enhancing efficiency in decision-making. Lastly, the connection between BD-enabled DC capabilities and decision-making is mediated by exploratory learning, as it promotes innovation, flexibility, and a proactive mindset, persuading organisations to enhance their strategic focus and adaptability in accordance with the environment's dynamics.

H4: Exploratory learning mediates the association between big data-enabled dynamic capabilities.

Figure 1: Theoretical Framework



Methodology

The method of data collection used in this research is the survey method. As the study aims to comprehend the role of big data analytics in enhancing the dynamic capabilities of organisations and the impact of such analytics on the quality of decision-making within organisations, it also examines the intervening role of exploratory learning. The personal and professional networks within the software industry were used as a tool for reaching the respondents. The research methodology employed in this study is a positivist research approach, which aims to investigate the causes and effects of using objective data and statistics to examine the relationship between them. Under this approach, the researchers conduct a neutral and objective study, using structured instruments to gather quantitative data. The research employs the deductive method of reasoning, which involves developing multiple hypotheses based on a previously established theoretical framework, and then verifying or refuting these hypotheses with the aid of empirical evidence (Saunders, 2009; Wilson, 2014).

It is a cross-sectional study. The target sample size (330) was based on the number of software houses in Pakistan. The organisational unit of analysis is the organisation. The data is gathered through a self-administered questionnaire from the owner, top management of the organisation, or its representative. The study sample is not known, as it is challenging to get a complete list of the software houses, both official sites of the "Pakistan Software Export Board (PSEB) and the Association of Pakistan Software Houses (PSHA)". A non-probability convenience sampling technique is employed, which enables the researcher to obtain responses from available participants, but not the entire population (Etikan et al., 2016).

Validated instruments were used to gather data in the literature that was employed. The questionnaire had demographic variables such as gender (male, female),age (20 or less,2120,3140,4150,51 or more), and years of work experience (2 or less, 25, 610,10 and above). It was a 5-point Likert question, in which the scale was 1-5, where the answers were "from strongly disagree (1) to agree (5) strongly".

The research design consisted of a self-administered questionnaire, which was distributed to a sample of respondents at the executive level who were employees in software companies through email. No instructions were given to reveal the names of respondents who wanted to remain anonymous, and respondents were informed that their information would be kept confidential. The number of collected data was measured in the largest cities of Pakistan, including Karachi, Islamabad, and Lahore, due to their consideration as leading IT centers where many established software firms are located. Other cities were also included to increase the diversity of the data.

The data generated was analysed using both descriptive and inferential statistical measures to refine the model and test the hypotheses. Structural Equation Modelling (SEM) will be applied as a method of testing the hypothesized theoretical model. One method to test the reliability of constructs will be confirmatory factor analysis (CFA), which will be used to assess convergent validity, and Cronbach's alpha coefficient, which will be employed to determine internal consistency. Cronbach's alpha should have a value of 0.70 or above (Hair et al., 2011).

Measures

The scales employed in the study to measure the variables of interest were previously made and tested. All items were measured using a five-point Likert scale (strongly disagree to agree strongly)or its opposite. Big data analytics-enabled dynamic capabilities were rated on a 10-item scale using the reports of Akter et al. (2016), Fosso Wamba et al. (2017), and Srinivasan and Swink (2018).The scale is used to assess an organisation's ability to utilise big data in sensing, integrating, and responding to both internal and external business environments.

The instrument used for measuring exploratory learning was designed based on the studies of Atuahene-Gima (2005), He and Wong (2004), Katila and Ahuja (2002), and Yalcinkaya et al.(2007) and consisted of five items. This construct concerned the way that firms bought and experimented with entirely new knowledge that traversed skills and technologies. For example, to what extent did our organisation acquire manufacturing technologies and skills not previously available within the firm, and to what extent did our organisation develop innovative skills in areas where the firm had no prior experience? This was a scale where responses were given on a five-point Likert scale of 1 (worst) to 5 (best).

Shamim et al.(2019) evaluated the quality of the decision-making process, both in terms of effectiveness and efficiency, with an 8-item scale. It is a measure that determines the standard of organisational decisions. Examples of areas where I believe we are making good decisions: Our cost of decision-making is very low, etc.

Along with the key constructs, the questionnaire included a demographic section in which the choices were on "gender (male, female), age (20 or less, 21-30, 31-40, 41-50, 51 or above), and the length of working experience (2 or less, 2-5, 6-10, 10 or above).

Empirical Results

This study tests the hypothesized model using Partial Least Squares Structural Equation Modeling (PLS-SEM) software, specifically WarpPLS 8.0.PLS-SEM is becoming increasingly popular and is widely utilized in modern modeling. Along with the inclusion of measurement error in the aggregation of latent indicators to calculate latent variables, one of the significant applications of PLS-SEM is its use in calculating latent variables. In comparison, covariance-based SEM is said to ignore measurement errors and works with weighted composite latent indicators (Kock, 2019).Additionally, PLS-SEM facilitates the estimation of the model by employing flexible assumptions that reduce complexity and maximise the theoretical parsimony of the model (Hair, Ringle, and Sarstedt, 2011). To anticipate the primary analysis, a preliminary analysis was undertaken to ensure that there were no problems related to multicollinearity, missing values, or outliers.

Measurement Model

The measurement model was the first step tested to examine its adequacy and quality measures. Table 1 indicates that the model's results are applied to the data and correspond to the required statistical limits. The Average Path Coefficient (APC) was 0.509, and the significance was found to be high($p<0.001$),indicating that the direct relationship hypothesized in the model is relevant and of moderate strength. The identical outcome can be said about the Average R-squared (ARS =0.554,$p<0.001$)and the Average Adjusted R-squared(AARS=0.552,$p<0.001$),which show that the model can explain about 55 per cent of the variance in the endogenous constructs, thus showing that the model has appropriate predictive power.

In the case of multicollinearity, the Average Block VIF(AVIF=1.856)and the Average Full Collinearity VIF(AFVIF=2.556)are significantly lower than the conservative threshold (5); therefore, there is no situation of multicollinearity in the model. Additionally, the Goodness-of-Fit (GoF) value was estimated to be 0.600, which is significantly larger than the threshold for a large effect size (0.36 or larger). It implies that the model is very explanatory, and the overall fit of the model is impressive.

Taken together, these indices provide relatively good indications that the measurement model is both statistically substantial and theoretically sound. The model exhibits a good goodness of fit and high explanatory power, and it lacks multicollinearity measures, which are reasons why the model is well-suited for testing further hypotheses through the structural model.

Table 1: Quality Indices and Model Fit

Index	Value	Criteria
Average path coefficient (APC)	0.509***	P<0.05
Average R-squared (ARS)	0.554***	P<0.05
Average adjusted R-squared (AARS)	0.552***	$P < 0.05$
Average block VIF (AVIF)	1.856	Acceptable$if <= 5, ideally <= 3.3$
Average full collinearity VIF (AFVIF)	2.556	Acceptable$if <= 5, ideally <= 3.3$
Tenenhaus GoF (GoF)	0.600	sin $a11 >= 0.1$,,medium $>= 0.25$,1arg $e >=$ 0.36
Simpson's paradox ratio (SPR)	1.000	Acceptable$if >= 0.7, ideally = 1$

The reliability and validity of constructs were tested after identifying the overall model fit,as illustrated in Table 2. All the constructs as shown in the findings are within the required limits and above, which illustrates a robust construct validation. The Composite Reliability (CR) scores were almost ideal, with maximum scores of 0.912 and 0.917 in Exploratory Learning and Exploratory Learning, respectively, which is very high in comparison to the minimum required value of 0.70.These values are a glorification of internal consistency. They can be used in the process of substantiating an adequate conclusion, which holds that the items contained in each construct consistently measure the same underlying dimension. Equally, the Cronbach's alpha values were also found to be high, ranging between 0.878 and 0.953, which once again surpasses the recommended value of 0.70, indicating construct validity.

The convergent validity review was conducted through the Average Variance Extracted (AVE).All the constructs exceeded the minimum AVE of 0.50 and consisted of: BDA-enabled Dynamic Capabilities (AVE=0.541),,Decision-Making Quality(AVE=0.566), and Exploratory Learning (AVE=0.842).These results indicate that the two constructs can account for over 50 per cent of the variability they explain. Additionally, the items in each of the constructs had a higher factor loading that exceeded 0.70, which is a high level of correlation between the indicator and the latent variable. It is worth noting that the intensities of the Explorative Learning items ranged from 0.907to 0.925, indicating a very high degree of reliability and convergent validity for this construct.

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According to the findings of Table 2, the measures are valid and reliable in the scales applied to approximate the constructs. The high CR and Cronbach's alpha values indicate excellent internal consistency. The AVE scores and the factor loadings are strong evidence of convergent validity. The findings support the validity and sufficiency of constructs to be employed in the subsequent stage of testing the structural model.

Table 2: Reliability and Validity

Construct	Item	Factor Loading	CR	a	AVE
Big Data Analytics enabled Dynamic Capabilities	BDAEDC1	0.701			
	BDAEDC2	0.729			
	BDAEDC3	0.628			
	BDAEDC4	0.794			
	BDAEDC5	0.761			
	BDAEDC6	0.792	0.922	0.905	0.541
	BDAEDC7	0.774			
	BDAEDC8	0.696			
	BDAEDC9	0.73			
	BDAEDC10	0.737			
Decision-Making Quality of an Organisation	DMQO1	0.794			
	DMQO2	0.805			
	DMQO3	0.78			
	DMQO4	0.749			
	DMQO5	0.716 0.912	0.89	0.566	
	DMQO6	0.704			
	DMQ07	0.724			
	DMQO8	0.741			
Explorative Learning	ELR1	0.925			
	ELR2	0.922			
	ELR3	0.924 0.964	0.953	0.842	
	ELR4	0.907			
	ELR5	0.909			

Following the reliability and convergent validity tests, discriminant validity was tested according to the Fornell-Larcker (1981) criterion. In Table 3, the outcomes prove that discriminant validity is highly validaed. It would be the square root of the Average Variance Extracted (AVE) of the individual constructs, which is shown on the diagonal line, and is larger than the correlation with other constructs. To illustrate, the square root of the AVE of BDA-enabled Dynamic Capabilities (0.736) is high compared to that of the correlation between BDA-enabled Dynamic Capabilities and Decision-Making Quality (r=0.661) and with Explorative Learning(r=0.632). Similarly, Decision-Making Quality, which is the square root of AVE (0.752), is higher than its relationships with BDA-enabled Dynamic Capabilities and Exploratory Learning. On the same note, the square root of the AVE value (0.788), as denoted in the Explorative Learning, provides the most significant value and is larger than the correlations involving the other two constructs. These findings suggest that all constructs are empirically distinct and the measures are not used to assess the same underlying construct.

Along with the discriminant validity, the proposed study has other hypotheses supported by correlation coefficients. Interrelationships may be described as positive and significant at the 0.01level, indicating that the relationships between the constructs are substantial and meaningful. Specifically, the correlation between Exploratory Learning and Quality of Decision-Making(r=0.695,p<0.01)remains remarkably high, which once again emphasizes the relevance of exploratory learning in enhancing the quality of organizational decision-making. Similarly, we observe that Dynamic Capabilities facilitated by BDA correlate with Decision-Making Quality (r =0.661,p=0.00)at a significantly higher level, indicating that better data-driven dynamic capabilities positively affect the quality of decisions made by an organisation. The empirical justification for the argument that BDA-enabled Dynamic Capabilities are moderately correlated with Exploratory Learning(r=0.632,p<0.01)is supported by the fact that big data capabilities are relevant in the process of acquiring new knowledge and exploratory learning.

Table 3 demonstrates that the results support the discriminant validity, in addition to confirming the theoretical assumptions of the model. The results suggest that the constructs are distinctive and firmly connected, which supports their inclusion in the model and confirms the assumption that learning processes can be manipulated with the help of BDA-based dynamic capabilities, subsequently influencing the quality of decision-making.

Table 3: Correlations and Square Root of AVEs

Construct	1	2	3
BDA-enabled DCs	(0.736)		
DMQO	0.661**	(0.752)	
Explorative Learning	0.632**	0.695**	(0.788)

***p<0.01,*p<0.05,BDA=big data analytics,DCs=dynamic capabilities.

Hypothesis Testing

The structural model of PLS-SEM was employed to test the hypotheses. Once the validity and reliability of the constructs have been established, Table 3 below shows the correlation between the variables. The findings indicate that Explorative Learning has a positive and significant relationship with BDA-enabled DCs. Moreover, both BDA-enabled DCs and learning have strong positive relationships with the Decision-Making Quality of Organisation (DMQO). These correlations have a statistically significant value of 0.01, indicating a strong and consistent relationship between the constructs. These findings confirm the suggested model as well as empirical evidence on the tested hypothesized paths in

Table 4: PLS-SEM Results

Hypothesis	Path Tested	Effect Size (β)	p-value	Supported
H1	BDAEDC→DMQO	0.638	<0.001	Yes
H2	BDAEDC→EXRL	0.642	<0.001	Yes
H3	DMQO→EXRL	0.687	<0.001	Yes
H4	BDAEDC→DMQO(via mediation)	0.442	<0.001	Yes

The results of the hypothesis testing, based on PLS-SEM, and the findings are presented in Table 4, providing strong empirical evidence to support the relationships proposed in the research model. The relationship between Big Data Analytics-Enabled Dynamic Capabilities (BDAEDC) and the Decision-Making Quality of Organisations (DMQO) exhibits a directional relationship, as supported by a path coefficient of 0.638($p<0.001$). The finding establishes that the more vibrant capabilities acquired by big data analytics enable organisations to be better placed to make informed and resourceful decisions, thereby improving the quality of the decision-making. H2promoted the idea that the positive impact of Dynamic Capabilities will be facilitated through BDA on Explorative Learning. This hypothesis also has a strong score (0.642,$p<0001$),indicating that organisations with high big data capabilities are better positioned to pursue new knowledge, innovative practices, and exploration-related activities. The conclusion shows that big data plays a central role in facilitating innovation-based learning in an organisation.

Hypothesis 3 tested the correlation between Exploratory Learning and Decision-Making Quality, and a significant positive effect was detected($p<0.001$,$r=0.687$).This means that exploratory learning is critical in ensuring that the quality of decisions made in the organisation is high, as it helps the organisation explore new opportunities, modify strategies, and seek new solutions.

Finally, the mediating role of Explorative Learning in the relationship between BDA-enabled Dynamic Capabilities and Decision-Making Quality was studied in Hypothesis 4 (H4). The indirect effect was also significant(0.442,$p<0.001$), which is in line with the partial mediation. This observation suggests that the ability to supervise capabilities facilitated by BDA would have both direct and indirect influences on the decision-making process, as the approach enables the exploration of the learning process.

Altogether, the results in Table 4 are convincing in supporting the model hypothesis. They demonstrate that dynamic capabilities can directly enhance the quality of decisions, encourage explorative learning, and indirectly, through mediating the nature of the learning processes, improve the quality of decision-making by BDA-enabled Dynamic Capabilities. These results also substantiate the theoretical assumption of the study that the connection between dynamic capabilities and organisational learning is the key to mobilising big data for high-quality decision-making.

Discussion

The study aimed to investigate the association between Big Data Analytics-enabled Dynamic Capabilities, Exploratory Learning, and the Quality of Decision-Making in Organisations. The results present a strong case for introducing the proposed model and contribute to the existing body of literature on the topic of big data and dynamic capabilities. The results of the measurement model indicated that the research fit well within the model, with all findings being statistically significant. The mnulticollinearity indices were at safe levels, with Tenenhaus GoF being greater than the substantial effect size level, thus ensuring the model's general soundness. The findings presented above indicate that the relationship between the hypotheses can be investigated appropriately using the proposed model, which provides a satisfactory description of the data.

It was also supported by a reliability and validity analysis, which ensured that the constructs used in this study are reliable and valid. Internal statistics, including composite reliability and Cronbach's alpha on each of the constructs, helped to attain statistical independence and were significantly higher than the recommended cut-off range. Likewise, convergent validity was also upheld, confirming the use of the AVE scores and the factor loadings. In contrast, discriminant validity was determined and confirmed through the Fornell-Larcker criterion, and the contrast between the two constructs was established. Combining the results ensures that the constructs utilised in the current study were presented similarly and adequately.

The results of the structural model showed that BDAEDC was an important and positive contributor to the quality of the decision made, and to learn to explore. It confirms that not only do organisations with well-developed capabilities, achieved through high-order big data, improve the quality of their decisions, but also facilitate learning processes that enable them to be experimental and innovative. Similar to earlier research (Mikalef et al., 2020; Seddon et al., 2017),the provided results highlight the source of competitive advantage offered by BDAEDC, which improves learning and decision-making outputs. In addition, the study found that exploratory learning has a profound and significant impact on the quality of decisions made. This supports the argument of March (1991) that exploration enhances the knowledge base of the firms and equips managers to make effective, efficient, creative, and responsive decisions.

Finally, the results of the mediation revealed that the connection between BDAEDC and the quality of decision-making is partially mediated by exploratory learning. It implies that, as the power of big data has a direct positive impact on decision-making results, it is also transmitted through learning processes, providing the possibility to experiment and explore new opportunities.

Theoretical Implications

This study offers several theoretical contributions to the existing knowledge on the application of big data analytics, the concept of dynamic capabilities, organisational learning, and decision-making. To begin with, the research enhances the Dynamic Capabilities View (DCV), as empirical validation demonstrates that Dynamic Capabilities based on Big Data Analytics (BDAEDC) significantly contribute to the quality of decision-making. This research provides empirical evidence that the combination of dynamic capabilities and big data has a positive influence on the quality of managerial decisions (Teece, 2007; Mikalef et al., 2020).

Second, the study on organisationaI learning demonstrates the mediating role of the explorative learning process between BDAEDC and the quality of decision-making. Although previous scholars have conceived the role of learning in terms of organisational adaptability (March, 1991; Helfat & Raubitschek, 2000), little has been done on the dynamics of learning with big data capabilities. As the research confirms that exploratory learning contributes significantly to mediating this relationship, BDAEDC not only influences the outcome of a decision by enhancing direct capability but also affects development by encouraging experimentation, innovation, and the acquisition of new knowledge.

Third, the paper is relevant to research on decision-making as it combines findings on organisational learning and the dynamic capability view. The findings indicate that data-driven technologies not only constitute a quality attribute for defining the quality of the decision-making process, but also require companies to develop skills in learning and experimentation.

Practical Implications

In addition to its theoretical implications, this paper has several practical implications for both managers and practitioners. Firstly, the results demonstrate that the dynamic capabilities enabled by BDA can play a crucial role in enhancing the quality of decisions made within an organisation. Managers should not simply focus on the technological side of investing in the latest data analytics technology, but also on dynamic capabilities, where management recognises, captures, and reconfigures resources to utilise such opportunities. These will help firms process raw data and convert it into actionable insights, enabling them to make effective and efficient decisions.

Second, the paper demonstrates that explorative learning is what needs to be promoted in companies. Managers should create an atmosphere that encourages experimentation, the acceptance of new knowledge, and the testing of new ideas. To enhance learning activities, it is suggested to introduce training programs, cross-functional collaboration, and knowledge-sharing systems to transform the gained information about big data into innovative solutions.

Third, it was established that the value of BDAEDC can be fully realized when learning-oriented practices complement it. It implies that companies ought not to consider the capacities of big data independently, but rather combine them with the rest of their organisational operations to encourage learning and knowledge generation. The leaders and decision-makers should then establish mechanisms for refining the quality of decisions made by creating ways of improving coordination between data analytics and exploratory learning programs.

Limitations and Future Directions

This study has its flaws, but it has strengths. Firstly, the research employed a cross-sectional design, which limits the study to examining the dynamic and changing experiences of BDA-facilitated dynamic capabilities, exploration, learning, and quality of decision-making over time. The process of development and transformation of such relations during various phases of organisational development can be studied in the future with the help of a longitudinal study.

Second, the data-gathering institutions were situated within a fixed regional and industrial setting. Since the results are helpful, they might not be applicable in any particular industry or geographical location. It would be beneficial to conduct this research in other cultural and industrial contexts to replicate the effectiveness of the proposed model and expand its scope of application.

Third, the focus of this analysis was put on the fact that explorative learning is a medium process between BDAEDC and the quality of decisions. Even though the results are good enough to argue on the same line of association, the results can still be improved by further research to identify more aspects of learning or organisational variables, including exploitative learning, absorptive capacity, or organisational culture, to have a better glimpse of the channels linked to big data capabilities and decision-making influences.

Finally, the survey instruments were based on self-reported data, which is prone to bias in answers. Researchers in the future may also adopt multi-source information, objective performance outcomes, or an experimental version to improve the validity of the research results. The removal of such restrictions will pave the way for a bright future of further expansion in the theoretical and practical developments outlined in this paper.

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