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## The Role of Big Data Analytics Capability to Achieve Competitive Advantage with the Mediation of Business Model Innovation: A Dynamic Capability View

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**Abstract:** The research aims to identify the function of big data analytics to attain competitive advantage through the mediation of business model innovation. 260 samples were taken from experts in Pakistan's manufacturing & service sectors. Data analysis was done using (Smart PLS). The findings demonstrate that big data analysis capability (BDAC) has a considerable impact on competitive advantage. By using big data, companies can make rational, data-driven decisions to satisfy customers, sustain and resilient supply chain management, low production costs, and efficient and effective business operations. Similar to how BC affects competitive advantage, business model innovation partially mediates this effect. Additionally, the influence of BDAC on both competitive advantages & new business model innovation is moderated by organizational IT infrastructure. This research presents a unique scenario of big data analytics in which firms use big data inside to innovate their established business models, resulting in considerable competitive advantage in emerging countries like Pakistan.

**Key Words:** Big Data, Competitive Advantage, Innovation, Dynamic Capability

### Introduction

Organizations in the current scenario of a more complex and uncertain business environment must engage in innovation; recreating and modifying their strategic capabilities to counter this environment from a dynamic capability theoretical view (Al-Darras & Tanova, 2022; Lerman et al., 2022; Ramadan et al., 2020). Only making capital investments will not be enough to compete; firms should have to create innovative capabilities that competing firms will find difficult to imitate (Dubey et al., 2018; Lerman et al., 2022; Shamim et al., 2019). As a direct result of the digital revolution, society is undergoing profound and rapid transformation. As a consequence of this, companies are looking for innovative methods to entice new customers, satisfy existing ones, and retain existing ones. The firms can attempt to gain a competitive

advantage by adopting innovative strategies (Shah, 2022). Organizations are using digital technologies such as big data techniques to create innovation in their businesses (Kubina et al., 2015; Manyika & Roxburgh, 2011; Wiener et al., 2020). It has the potential to enhance firms' competitive advantages by improving data-driven performance (Ciampi et al., 2021a; Ramadan et al., 2020).

A firm's underlying framework may be described as its "business model." (Naomi et al., 2016); a description of the strategies that your organization plans to use to generate value in the market (Geissdoerfer et al., 2018). It comprises the underlying organization of people as well as the operational infrastructure that individuals use to get their tasks done (Ciampi et al., 2021a; Rachinger et al., 2019). Innovating business models has become essential for survival in the

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competitive world (Garzella et al., [2021](#)). Business models are made to fulfil consumers' needs. All strategies of the business are kept aligned with the business model (Spieth et al., [2019](#); Veile et al., [2022](#)).

Big data enables the provision of useful information to execute fully data-based business models (Ghasemaghahi & Calic, [2019](#)). Modern data analytics tools can identify the root causes of production system variance and develop countermeasures to increase system stability and save costs. (Cochran et al., [2016](#)) Firms can effectively foresee market requirements by using BDA approaches; as a result, they can innovate and adapt their business model strategies (Gupta et al., [2020](#)). The business environment is rapidly changing; therefore, it is difficult to sustain innovative ideas without data analysis (Bocken et al., [2014](#); Geissdoerfer et al., [2018](#)). Competitive advantage is crucial for the success of strategic decisions and management (Dahiya et al., [2022](#); Sigalas, [2015](#)). By using big data and innovative business techniques, a competitive advantage can be gained (Ciampi et al., [2021b](#); Dahiya et al., [2022](#)).

This study examines the relationships between big data analytics, business model innovation, and competitive advantage under the moderating effect of organizational IT infrastructure. In today's database knowledge-intensive economy, information technology (IT) is one component that cannot be overlooked. Without effective information technology, effective big data management is not conceivable (Saeidi et al., [2019](#)). Organizational IT infrastructure is an essential building block for firms that seek to maximize the potential of emerging digital technologies (Klotins & Peretz-Andersson, [2022](#)). Firm processes, networks, and organizational and technical components establish an IT infrastructure (Joglekar et al., [2022](#)). IT infrastructure is identified in the research literature as the linkage of various system collections such as software, hardware, standard procedures, the Internet, and very important people (Hustad & Olsen, [2021](#)). To facilitate the integration of their internal business

processes, firms need IT strategies and procedures that may increase productivity, become more efficient, and react quickly to customer needs (Jha et al., [2020](#)). To successfully achieve and sustain competitive advantage, firms must develop a proper IT infrastructure, which lays a technological foundation for innovation and competitiveness through advanced data analytic capabilities like big data. The ability of an organization to adapt to change is a crucial aspect in the development of big data analytics capabilities. It can be impossible to build big data analytics if the current IT infrastructure is wholly incompatible with it, as managers are not able to make data-driven decisions, and are also unable to operate the systems (Rialti et al., [2019](#)). Companies are using big data in the decision-making process (Gupta et al., [2021](#)). Companies spend their significant budgets on IT, digitalization, and data analytics (Grover et al., [2018](#)). Any amount of data is worthless if you don't have proper infrastructure and people who know how to make use of it (Wicaksana, 2016). So big data analytics as a resource capability provides a common pool of information technology (IT) resources for innovation, which is the most critical criterion in achieving competitive advantage.

The business process is increasingly changing due to the prevalence of digitalization, advancement in information technology, the Internet of Things, and big data analytics. Therefore, the adoption of these elements is essential, along with a refined and innovative business model. (Parida et al., [2019](#)). The IT infrastructure of an organization strategically affects its capability to utilize advanced data analytics to innovate its business models (Ciampi et al., [2021b](#); Rehman et al., [2020](#)). Even though big data analytics (BDA) advancements offer tremendous commercial value and useful business insights, many organizations find it challenging to benefit from their BDA endeavours (Dahiya et al., [2022](#)). However, many organizations are still not utilizing the full potential of big data analytics as a resource capability (Tabesh et al., [2019](#)).

To fill this gap, we create a framework to examine the relationship between big data analytics as an independent variable and competitive advantage as a dependent variable while taking into consideration the strategic role of business model innovation as a mediator. Additionally, we also examine the moderating effect of a firm's IT infrastructure with BDA on business model innovation and competitive advantage separately. A huge volume of data termed Big Data, was collected in organizations, but unable to analyze and interpret the data for strategic decision-making in this competitive market, which is of great concern for the industrial sector (Awan et al., 2022). The subject of how firms may improve their competitive advantage by utilizing big data analytics capability with the mediating role of business model innovation has not been addressed by the current literature, although it has identified the factors that affect the competitive advantage and firm performance through big data (Al-Darras & Tanova, 2022). This study aims to provide an answer to the question "How can big data analytical enhance competitive advantage, and how can business model innovation contribute to competitive advantage?" based on the discussion above.

## Literature Review

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### Big Data Analytics

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There is great importance to researching big data analytics (Dubey et al., 2019). Information flows within and across organizations have become crucial for the survival of business growth (Ciampi et al., 2021b). Big data and predictive analytics capability are regarded as two of the most important organizational resources in the age of digital transformation (Al-Darras & Tanova, 2022). If organizations can explore value by utilizing the potential of big data, big data may be an extremely useful resource capability for them. The development of technologies like big data analytics is providing new horizons for firms to give value to their consumers in terms of cost-effectiveness (Åström et al., 2022; Toufaily et al., 2021). Dynamic capabilities, or DCs, are

practical, simple, and flexible procedures that depend on quickly developed new insights to facilitate the transformation, combination, or renewal of resources and competencies into capabilities that are required for ambiguous markets in a highly uncertain world (Eckstein et al., 2015; Eisenhardt and Martin, 2000). According to the above ideas, BDA is viewed as a dynamic capability that arises from an organization's ability to reconfigure firm-level resources (Wamba & Ren, 2017).

### Competitive Advantage

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Porter (1985) claims that corporations can achieve a competitive advantage by finding and implementing generic strategies, and he discusses the interaction between several types of competitive advantage—cost and distinctiveness—and the breadth of a firm's activities. "A corporation is said to have a competitive advantage when it is implementing a value-creating strategy that is not being executed by any present or potential competitors," according to Barney (1991, p. 102). According to Peteraf (1993), the capacity of an organization to maintain above-average returns is referred to as a competitive advantage. According to Reed and DeFillippi (1990), competitive advantage can be used for various purposes (Hinterhuber, 2013).

### Business Model Innovation

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A company's "business model" is essentially a summary of its "business structure." (Baden-Fuller & Morgan, 2010). The literature has highlighted three key BM dimensions: value creation, value proposition, and value capture (Clauss, 2017). BMI may be described as the process of consciously changing one or more components that are fundamental to the business value logic for the benefit of the organization, its clients, and any other relevant stakeholders. (Bucherer et al., 2012). It is necessary to take full advantage of disruptive technologies since developing innovative technological solutions is just as important as coming up with new business models

(Åström et al., 2022). A business model offers the framework for how an enterprise grows and delivers value to customers, as well as the strategies employed to gain a component of that value.

(Rachinger et al., 2019). Business model innovation (also known as BMI) is the primary strategy for overcoming external difficulties through the process of developing the foundation of a company. (Kraus et al., 2022).

## **Big Data Analytics and Competitive Advantages**

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BDA has been recognized as a viable instrument for strengthening firms' competitive advantage by improving data-driven performance (Ramadan et al., 2020). Big data analytics, when used as a dynamic capability, can be used to generate knowledge that is relevant to business, provide value, improve performance, and give a firm an advantage over rivals in a dynamic market (Singh & Del Giudice, 2019). Firms that successfully utilize the digitalization potential of IT infrastructure powered by big data and analytics will outperform their rivals in terms of revenue growth and operational effectiveness (Cappa et al., 2021; Parida et al., 2019). According to Chen et al. (2012), big data presents a huge possibility for gaining a competitive advantage. BDA results that include custom applications and firm internal data will provide high-level firm-specific knowledge and could lead to a long-term competitive advantage (Dahiya et al., 2021). This discussion leads to the hypothesis:

**H1:** BDA has a positive effect on Competitive Advantage

## **Big Data Analytics, Business Model Innovation, and Competitive Advantage**

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The availability of BDA, in particular, allows companies to tap into the value of useful insights and information generated from diverse, large-scale, and up-to-date information in the form of data about consumers, competitors, and markets (Ghasemaghaei et al., 2019) to fully implement

and apply data-driven business models (Manyika et al., 2011). Firms may accurately foresee market requirements and, as a result, change their strategies and structures to satisfy evolving markets' wants and reveal upcoming market goals by employing BDA approaches (Gupta et al., 2019). The key benefit of data-driven BMI is the capacity to rationalize management's intuitions and inventiveness by providing rapid and ongoing access to new information about business stakeholders (Cheah & Wang, 2017).

BMI is found to be a strong predictor of competitive advantage (Porter's competitive strategy). Because rivals promptly imitate a company's strategy if it suffers from BMI, businesses must frequently alter their BM to gain a stronger competitive advantage. (Mitchell and Coles, 2003). In contrast to SMEs with reactive BMs, those with updated and proactive BMs increase their value and attract more customers in dynamic marketplaces. (Hacklin et al., 2017; Shahzad et al., 2017). The main forces behind the company's sustainability and values are cost reduction, risk reduction, reputation, brand image, attractiveness for employees, and new skills that BMI can cover. (Schaltegger et al., 2012).

This discussion leads to the hypothesis

**H2:** BMI positively mediates between BDA and Competitive Advantage

## **The moderating effect of Organizational IT Infrastructure**

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The importance of information technology (IT) in today's economic and commercial environment cannot be denied. Business firms can now use IT for marketing, sharing information on many platforms, data transformation, monitoring, quality control, e-commerce, etc. (Massachusetts, 2002). In addition, IT is considered a tool to increase competitive advantage (Mao et al., 2016; Marinagi et al., 2014). If a company learns that its competitors are employing digital technology like big data, it will experience a crisis as it realizes that without big data analytics, it will

soon lose its competitive advantage (Chen et al., 2015). Furthermore, past research has shown that the stronger a company's IT capabilities are, the more likely it is to adopt new technologies (Kuan and Chau, 2001; Kamal, 2006). As a result, it is thought that a company's IT infrastructure and competencies can boost the likelihood of BDA adoption. The above discussion leads to the following hypotheses for testing:

**H3:** Organizational IT infrastructure moderates the effect of BDA on Competitive Advantage

Increased digitalization and sophisticated IT infrastructure have had an impact on business models because they have allowed companies to collaborate in new ways, leading to the development of new products and services as well as new channels for communication with clients and staff. (Rachinger et al., 2019). Simultaneously, increasing digitization has increased pressure on companies to assess their current approach and extensively research new business opportunities (Bouwman et al., 2019; Rachinger et al., 2019).

The following hypothesis is derived from the above discussion:

**H4:** Organizational IT infrastructure moderates the effect of BDA on BMI

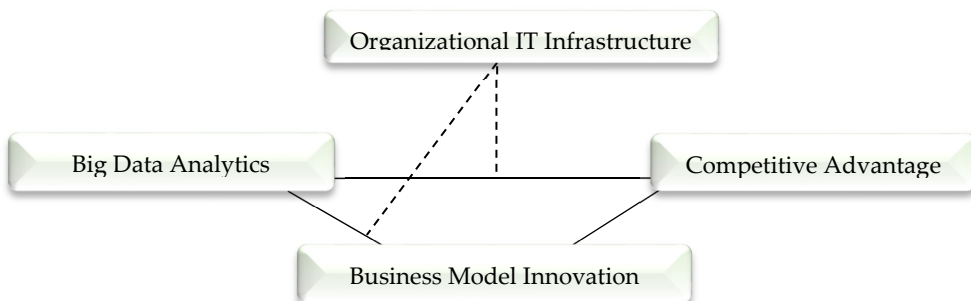
### Theoretical underpinning

The dynamic capability theory (DCT) is used to describe the underlying relationship between the variables in this research. It highlights the effect of BDA on a firm's competitive advantage

through the mediating role of BMI. The Dynamic Capability (DCT) theory originated as a theoretical addition and extension of the resource-based view (RBV) theory to describe how organizations manage to stay competitive in unpredictable circumstances throughout time (Ambrosini & Bowman, 2009). According to the fundamental idea of the resource-based view theory, a company's success is determined by the accessibility and organization of unique, inimitable, non-substitutable, and valuable assets, which permit the adoption of value-creating strategies for a firm (Barney, 1991). A corporate firm can achieve a long-term competitive advantage by obtaining and controlling strategic resources and, as a result, establishing firm-specific skills that are extremely dependent on the types of resources gathered (Makadok, 2001). In recent times, research has shown that the RBV's static. The approach falls short of understanding how firms use their resources and capabilities in dynamic marketplaces, opening the door for the DCV's widespread adoption (Priem & Butler, 2001). The dynamic capabilities theory (DCT) suggests that firms should be skilled in recreating and renewing their competitive strategies and capabilities to be in a competitive position to meet the challenges of a dynamic and uncertain environment (D.J. Teece et al., 1997; G. Linden et al., 2018). DCs enable firms to build unique organizational and strategic routines and skills that are critical to their continued success and the creation of new markets (Fornell & Larcker, 1981).

**Figure 1**

*Conceptual Model*



The dynamic capability and resource-based theory provide the theoretical underpinnings of the above theoretical framework. The relationship depicted in Model IV, DV, has been taken from the previous literature, as mentioned above. However, the mediating and moderating variables shown in Figure 1 have been tested separately for all variables. However, the current model is unique as the relationship between mediating and moderator has not been tested before in the Pakistani context. This unique model has been developed by the author.

### Methodology

This study's methodology was precisely developed to ensure rigour. The research philosophy used in this study is positivism with a cross-sectional survey-based and quantitative design (Alharahsheh et al., 2020). This research used a deductive approach, relying on theoretical explanations based on observable events and hypothesis testing. This strategy is used to establish a causal link between variables, test hypotheses, and generalize the regularities of human social behaviour (Saunders et al., 2007). To support us in data collection, we contacted professionals in the manufacturing and service industries with field experience of at least 1 year, working in both multi-national and national firms. The manufacturing sector contributes 19.3% and the service sector contributes 58 % to the GDP of Pakistan (Pakistan Economic Survey, 2022) In today's world, both the service and industrial industries are being afflicted by a digital tsunami. (Zhong et al., 2016) The questionnaire consisted of 33 items, and to access our theoretical model, 268 samples were gathered all over Pakistan's manufacturing and service industries in November and December 2023. Structural Equation Modeling (PLS-SEM) was chosen as the statistical analysis method since it has both explanatory and predictive

power and can be used for non-normal data distribution.

### Measures

The survey questionnaire is based on 4 parts; BDA, organization IT infrastructure, BMI competitive pressure, competitive advantage, and type of industry. BDA, which is a study of the second-order independent variable and its construct items, was adopted and assessed (Dubey et al., 2018). Each item of BMI, which is a study mediating variable, was adopted and assessed (Ciampi et al., 2021b). A competitive advantage, which is a study-dependent variable, and its construct items were adopted and assessed (Abeysekara et al., 2019). Each item of the organization's IT infrastructure, which is a study moderating variable, is evaluated and assessed (Yuanyuan et al., 2017). All items of the above-mentioned variables were evaluated by respondents on a Likert scale from 1 (strongly disagree) to 5 (strongly agree). Industry type, which is a categorical variable, is taken as a control variable in this study.

### Results

The results and discussion chapter presents in detail the results from the data analysis. PLS-SEM analysis contains measurement and a structural model. The measurement model analyzes the reliability and validity of the constructs. The relevance of proposed linkages is ascertained using the structural model.

### Sample Description and Demographics

The information was gathered between 01 Nov 2023 and 05 Dec 2023. The questionnaire was floated through Google Forms to 350 people. Out of 268 responses received, 8 were not filled out properly, therefore 260 responses were analyzed. Details are given below:

**Table 1**

*Demographic Profile*

		Frequency	Percentage (age)
<b>Designation</b>	Staff Level Manager	12	4.5

	Lower Level Manager	66	24.7
	Middle-Level Manager	95	35.6
	Senior Level Manager	77	28.8
	Top/ Executive Level	17	6.4
	Total	267	100
	1-5 years	106	39.8
	6-10 years	56	21.1
<b>Job Experience</b>	11-15 years	40	15.0
	16-20 years	45	16.9
	Above 20 years	19	7.1
	Total	266	100
	Matriculation	01	0.7
	Intermediate	01	0.7
<b>Education</b>	Graduate	110	41.0
	Masters	156	58.2
	Total	268	100.0

### Common Method Bias (CMB)

Harman's single-factor analysis revealed that there was no common method bias variance because the highest-ranking factor only

explained 66.1 % of the variation (Podsakoff et al., 2003). CMB was next evaluated and ruled out since the latent variables' factor level variance inflation factor (VIF) was likewise less than 3.3 (Kock, 2015), as shown in Table 3.

**Table 2**

*Full Collinearity Test*

Construct	VIF
BDA	2.081
BM	2.292
CA	2.473

*Note: Summary of VIF of all the variables regressed on a random variable*

### Measurement Model

According to Sarstedt et al. (2019), researchers have proposed the two-stage approach as an alternative to the repeated indicators approach. In the context of PLS-SEM, higher-order constructs (also known as hierarchical component models) provide a framework for researchers to model a construct on a more abstract dimension (called a higher-order construct) and its more concrete sub-dimensions (referred to as lower-order constructs).

### Second-Order Reflective Measurement Model

Create and estimate the model that connects all of

the lower-order components in the first step (including exogenous and endogenous constructs). The reflecting measurement models of the lower-order components are the focus of the model evaluation initially. In stage two, you develop and estimate the stage two models using the latent variable scores of the lower-order components from stage one. Locate the higher-order constructs of the lower-order constructs' scores and add them as new variables to the dataset for this purpose. The results are comparable to those obtained using the repeated indicators approach, with the path coefficient estimates differing somewhat. The second stage's evaluation begins with a focus on the higher-

order component's reflective measurement model. See the lower-order construct loadings for the higher-order construct, then use the coefficients (loadings) to analyze the composite reliability and average value extracted, allowing us to build indicator reliabilities and AVE. These results establish the reliability and convergent validity above the crucial value of 0.5 Cronbach's alpha, as well as the composite reliability, and

average value extracted.

The reliability and validity of the item and constructs are calculated by testing the measurement model. The composite reliability, convergent validity, and discriminant validity are above the prescribed threshold values (Joseph F. Hair et al., 2019). Detail has been given in Table 3 and Table 4 below

**Table 3**

*First-Order Reflective Measurement Model Outer loadings, Composite-Reliability and Average-Variance Explained (Convergent-Validity)*

<b>Constructs</b>	<b>Items</b>	<b>Outer Loadings</b>	<b>Composite Reliability</b>	<b>Average Variance Extracted (AVE)</b>
Business Model Innovation	BM1	0.773	0.914	0.681
	BM2	0.849		
	BM3	0.864		
	BM4	0.789		
	BM5	0.847		
Competitive Advantage	CA1	0.804	0.904	0.612
	CA2	0.835		
	CA3	0.796		
	CA4	0.792		
	CA5	0.772		
	CA6	0.686		
DDDMC	DC1	0.753	0.869	0.571
	DC2	0.835		
	DC3	0.727		
	DC4	0.702		
	DC5	0.755		
Managerial Skills	MS1	0.792	0.914	0.640
	MS2	0.801		
	MS3	0.766		
	MS4	0.821		
	MS5	0.834		
	MS6	0.784		

Discriminant validity is established based on the hetero-trait–monotrait ratios. For each construct, the HTMT ratio is less than 0.90 (Henseler et al., 2015). HTMT ratio is based on the estimation of

the correlation of the construct. The HTMT ratio results in Table 4 below show that all HTMT ratios are less than the required threshold of 0.9 except the BDA construct.



**Table 4**

*Discriminant Validity*

	BDA	BM	CA	DC	MS	TS
BDA	0.00	0.00	0.00	0.00	0.00	0.00
BM	0.649	0.00	0.00	0.00	0.00	0.00
CA	0.57	0.703	0.00	0.00	0.00	0.00
DC	0.964	0.664	0.699	0.00	0.00	0.00
MS	1.003	0.596	0.456	0.773	0.00	0.00
TS	0.998	0.552	0.464	0.745	0.837	0.00

**Abbreviations:** BDA; Big Data Analytics, BM; Business Model Innovation  
 CA; Competitive Advantage, DC; Data Driven Decision Making Culture  
 MS; Managerial Skills, TS; Technical Skills

Multicollinearity between constructs was checked through collinearity statistics and VIF values in PLS-SEM. A previous study revealed that for a reasonable degree of multicollinearity,

the variance inflation factor (VIF) must be less than 3.3 (Hair et al., 2016). We found that all VIF values were less than 3.3, indicating that there are no difficulties with collinearity.

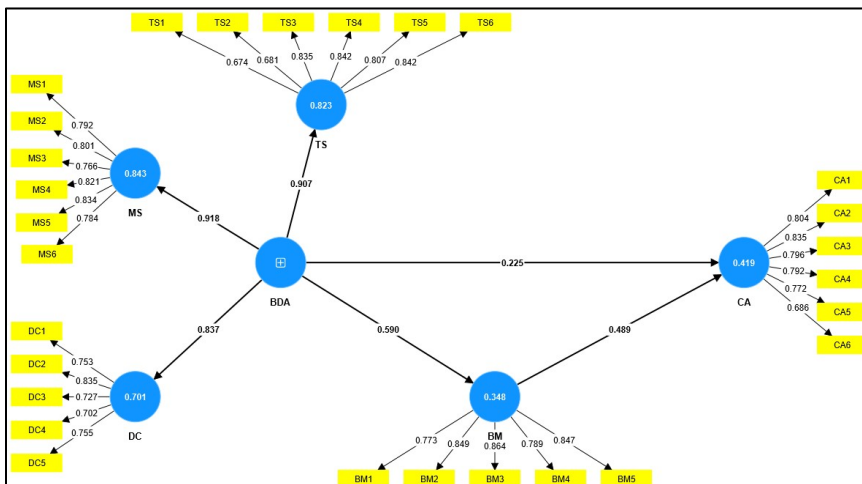
**Table 5**

*Collinearity Statistics (VIF)*

	BDA	BM	CA	DC	MS	TS
BDA	0.00	1.00	1.533	1.00	1.00	1.00
BM	0.00	0.00	1.533	0.00	0.00	0.00
CA	0.00	0.00	0.00	0.00	0.00	0.00
DC	0.00	0.00	0.00	0.00	0.00	0.00
MS	0.00	0.00	0.00	0.00	0.00	0.00
TS	0.00	0.00	0.00	0.00	0.00	0.00

**Figure 2**

*First-Order Reflective Conceptual Framework*



## Second-Order Reflective-Measurement Model

As part of the measurement model validation, the second or highest-order constructs were also validated. Each of these constructs was evaluated for reliability and convergent validity. Sarstedt et al. (2019) proposed that the higher-order construct be examined for discriminant validity with other lower-order constructs in the research.

According to the results, the reliability and validity of the higher-order constructs have been established. For all other constructs, reliability and convergent validity are established when the reliability value is greater than 0.70 and the AVE is greater than 0.50, respectively (Table 5). Discriminant validity of the higher-order construct with lower-order constructs is also tested in addition to reliability and validity.

**Table 6**

*Second-order Reflective Measurement Model*

*Outer -Loadings, Composite-Reliability, and Average-*

Construct	Items	Outer Loadings	Composite Reliability	Average Variance Extracted (AVE)
BDA	DC	0.883	0.918	0.788
	MS	0.894		
	TS	0.885		

*Variance Explained (Convergent Validity)*

Discriminant validity with other lower-order constructs is established using the HTMT

criterion, which is less than 0.90 (Henseler et al., 2015) as shown in Table 6 below.

**Table 7**

*Second-Order Reflective Measurement Model*

*Discriminant Validity (HTMT Ratios)*

	BDA	BM	CA		
BDA	0.00	0.00	0.00		
BM	0.678	0.00	0.00		
CA	0.606	0.703	0.00		
	BDA	DC	MS	TS	
BDA	0.720	0.766			
DC	0.836				
MS	0.929	0.651	0.825		
TS	0.920	0.673	0.608	0.868	

Figure 3 (a)

Second-order Reflective Measurement Model

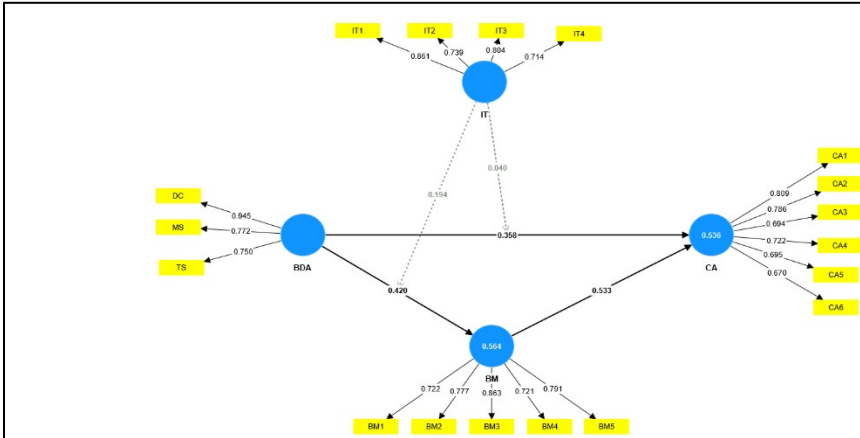
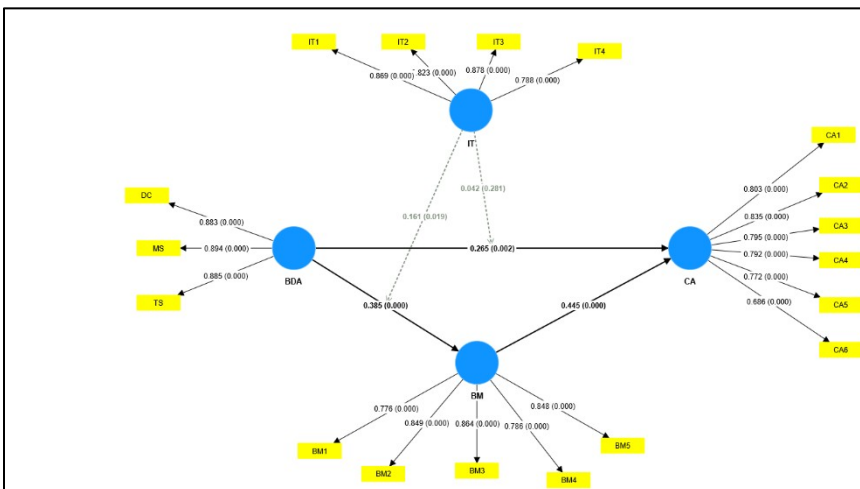


Figure 3 (b)

Second-order Reflective Measurement Model



**Structural-Model Measurement**

The evaluation of the structural model is the subsequent phase in the evaluation process, as depicted in Figure 2 above. In order to assess the statistical significance of the PLS-SEM results, bootstrapping with 5000 iterations was utilised for the development of the structural model. These included the structural path coefficient

(beta), R2, Q2, and f2 values. The prediction ability and model fit were assessed using R2 and Q2 values. The coefficient of determination R2 was employed for each endogenous variable in the model to assess the quality of the generated structural equation model (SEM). The coefficient of determination (R2) for the dependent variable BMI is 0.564, whereas for the dependent variable

competitive advantage, it is 0.536, as indicated in Table 7. The R2 value exceeds 0.2, indicating that the model possesses an adequate level of explanatory capability for the fluctuations observed in the dependent variables (Hair et al., 2016). The data presented in Table 7 clearly demonstrates that both BDA and BMI account for a significant 53.6.1% of the variability seen in competitive advantage. The BDA accounted for 56.4% of the variability in BMI, indicating a significant relationship.

In addition to the goodness-of-fit measurements, the effect size coefficients (f2) were utilised to evaluate the suitability of the developed model in Figure 2. Based on the findings of Hair et al. (2017), the effect size f2

values of 0.02, 0.15, and 0.35 represent minor, medium, and large effects, respectively, for endogenous latent variables. These values are reported in Table 7. All other f2 values above the range of 0.02, indicating acceptable levels of impact size. Furthermore, the blindfolding technique was utilised to assess the model's anticipated accuracy (Akter et al., 2011). The route model's predictive significance is satisfied if the Q2 value for a reflecting endogenous variable is greater than zero (Sarstedt et al., 2017). Table 7 demonstrates that the predictive relevance of the constructs was over zero, which is within the allowed range for all endogenous components, hence establishing predictive relevance.

**Table 8**

*Total effect size (f<sup>2</sup>), coefficient of determination (R<sup>2</sup>), and predictive relevance (Q<sup>2</sup>)*

	Total effect size (f <sup>2</sup> )		coefficient of determination (R <sup>2</sup> )	Predictive relevance (Q <sup>2</sup> )
	BMI	CA		
BDA	0.105	0.065	-	-
BMI	-	0.267	0.564	0.397
CA	-	-	0.536	0.251

The next step is structural-equation modelling, which is an assessment of the hypothesized relationship to substantiate the proposed hypotheses.

### **Direct Effects**

To test the hypotheses, the inner model is evaluated using boot-strapping with 5000 subsamples. The hypothesized direct impact path-coefficients, T values, effect size, and supported or not decision are summarized in Table 9. H1 evaluates whether BDA has a significant impact on the competitive advantage or not. The results revealed that BDA has a significant effect on competitive advantage ( $\beta = 0.265$ ,  $T=2.851$ ,  $p = 0.002$ ). Hence, H1 is supported in this case. The exogenous variable's contribution to R<sup>2</sup> is represented by the effect size f<sup>2</sup>; the value of 0.02 is considered a small-size effect, 0.15 is considered a medium-size effect, and 0.35 is considered a large-size effect (Hair et

al., 2016). In this model, all supported hypotheses have a small but statistically significant impact size.

### **Mediation (Indirect) Effect**

One simple mediation path is included in the proposed model. The result shows that the mediation's indirect effect is supported. A mediation analysis was performed to assess the mediating role of BMI. BMI mediates between BDA and competitive advantage. The results in Table 9 below, revealed a significant ( $p = 0.000$  and  $\beta = 0.171$ ) partial mediating role of BMI.

### **Moderation Effects**

The moderation results in Table 10 confirm the hypothesis (H3) that IT infrastructure moderates the effect of BDA ( $p=0.021$ ,  $\beta = 0.421$ ) on competitive advantage, but on the other side firm IT infrastructure ((H4), also moderates ( $p=0.019$ ,  $\beta = 0.161$ ) the effect of BDA on business model

innovation BMI as shown in table 9.

**Table 9**

*Direct Effects, Indirect Effects, and Moderating Effects*

Relationships value Decision	Beta coefficient	Std Error	T-Statistics	Confidence Interval		P-value
				5%	95%	
<b>Directs Effect</b>						
BDA → CA <b>Supported</b>	0.265	0.093	2.851	0.117	0.423	0.002
<b>Indirect Effect</b> (Mediation)						
BDA → BMI → CA <b>Supported</b>	0.171	0.044	3.905	0.102	0.246	0.000
<b>Moderation Effects</b>						
BDA*IT → CA <b>Supported</b>	0.421	0.047	2.579	0.074	0.166	0.021
BDA*IT → BMI	0.161	0.077	2.077	0.149	0.018	0.019 <b>Supported</b>

*Note: Relationships of independent variables with the dependent variable*

*Abbreviations: BDA: Big Data Analytics, BMI: Business Model Innovation*

*CA: Competitive Advantage, IT: Organizational IT Infrastructure*

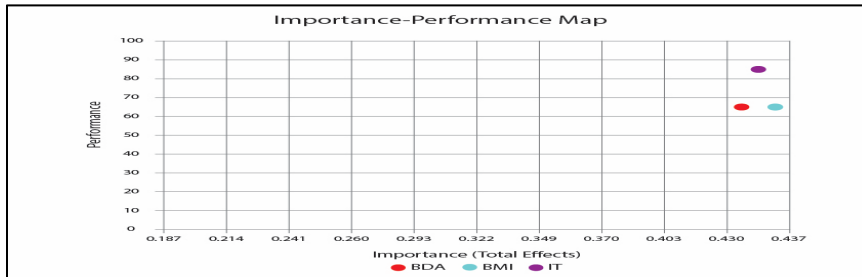
### **Importance Performance Map Analysis (IPMA)**

The importance-performance map analysis is an innovative method for presenting PLS-SEM results in Smart PLS version 3. It is commonly employed to evaluate the effectiveness of crucial aspects that contribute to the success of a firm. The x-axis represents the "importance" or overall impact of business success drivers, measured on a scale from 0 to 1. The y-axis represents the "performance" of these drivers, measured on a scale from 0 to 100. Subsequently, researchers can utilise this data to pinpoint past structures that have a substantial overall impact (high Importance) but exhibit low average latent

variable scores (bad performance). This knowledge can be applied to enhance operational efficiency in the future (Joe F Hair et al., 2018). Figure 3 illustrates that in this model, Organisational IT infrastructure holds greater significance and exhibits higher performance compared to BDA (Big Data Analytics) and BMI (Business Model Innovation). Managers should not underestimate the importance of this area in order to achieve a lasting competitive advantage. The combination of big data analytics and business model innovation has a significant impact on both importance and performance, playing a crucial role in achieving a competitive advantage.

**Figure 4**

Importance - Performance Map Analysis



**PLS-Predict**

When it comes to predicting model parameters for new observations, explanatory modelling is not very reliable (Hair & Sarstedt, 2021). On the other hand, predictive power refers to a model's ability to make reliable predictions for new observations (Shmueli & Koppius, 2011). The model was tested to see if it could have predictive

relevance. As shown in Table 9, for all dependent variables, PLS-SEM  $Q^2_{predict}$  is larger than zero except for four indicators. All of the PLS-SEM indicators had a lower RMSE (prediction error statistic) than the linear model. As a result, the model's medium predictive potential is determined (Shmueli et al., 2019) through this analysis.

**Table 10**

PLS Predict

Item	PLS-SEM		LM	PLS-SEM - LM
	RMSE	$Q^2_{predict}$	RMSE	RMSE
BM3	0.878	0.266	0.898	-0.02
BM2	0.835	0.262	0.85	-0.015
BM4	0.801	0.311	0.812	-0.011
BM1	0.91	0.212	0.911	-0.001
BM5	0.83	0.291	0.846	-0.016
CA2	0.866	0.182	0.851	0.015
CA5	0.818	0.159	0.784	0.034
CA4	0.949	0.095	0.92	0.029
CA3	0.875	0.156	0.876	-0.001
CA6	0.88	0.168	0.871	0.009
CA1	0.926	0.158	0.927	-0.001

Note: RMSE of endogenous items of the PLS sample model and linear model.

Abbreviations: BM; Business Model Innovation CA; Competitive Advantage

**Discussion**

Overall, in this study, we demonstrated how big data analytics capability, business model innovation, and organizational IT infrastructure

can be effectively utilized in advanced data analytics and innovation for the attainment of competitive advantage. Having the firm resources to compete is not so essential but

effective utilization of these resources is much more important to generate significant value from those resources (Barlette & Baillette, 2022). Particularly in a dynamic and uncertain environment, firms need to reconfigure their present capabilities; that is the key argument of dynamic capabilities theory (Shamim et al., 2019). This study examined how dynamic capabilities development can be influenced by big data analytics, business model innovation, and organizational IT infrastructure that leads toward sustainable competitive advantage.

The findings of our study corroborate the findings of earlier research by showing a favourable and substantial association between big data analytics and competitive advantage (Dahiya et al., 2022; Ramadan et al., 2020). Furthermore, the relationship between BDA and CA is strengthened by the moderating function of IT infrastructure and capabilities, which also offers the technological basis for this fruitful partnership.

There is potential for businesses to leverage big data analytics as a resource capability, according to theoretical literature about the relationship between big data analytics and business model innovation (Ciampi et al., 2021b; Rachinger et al., 2019). Furthermore, organizations may benefit from the theoretical literature's examination of the connection between business model innovation and competitive advantage (Anwar, 2018; Azeem et al., 2021; Ramadan et al., 2020). Nevertheless, in empirically based research, the moderating function of IT infrastructure with BDA on BMI and CA and the mediating role of business model innovation between BDA and CA remain to be investigated. Big data analytics and competitive performance have been found to be directly and favourably correlated by this study, which supports the theoretical perspective of dynamic

capabilities theory, which views big data analytics as a resource capability in an unpredictable and dynamic business environment (Ramadan et al., 2020).

## Conclusion

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The enormous interest that practitioners and scholars have shown in the big data phenomena served as a major driving force behind our study. This research work adds to the growing body of empirical research on the value of strategic and innovation management's ability to effectively utilize business development practices in the current scenario of the uncertain, complex, highly competitive, and dynamic environment of doing business. By making use of big data, businesses can make choices that are rationally based on data to satisfy consumers, maintain and strengthen supply chain management, maintain low production costs, and ensure efficient and successful corporate operations in the manufacturing and service sector of Pakistan.

It also demonstrates how business firms' efforts to create adaptable technological frameworks and innovative big data analysis capabilities support a corporate data-driven culture that can facilitate the adoption of various business model innovation processes. Moreover, it reveals that business model innovation has a positive and partial mediation role in the relationship between big data analytics and competitive advantage, indicating that the availability of sufficient big data resources and capabilities encourages the adoption of a strategic business model innovation inclination characterized by high levels of creativity, resiliency, and risk-taking, which, in turn, makes it easier to compete successfully in the market of the more dynamic, complex and highly competitive business environment.

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