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Research paper

Examining The Influence of Various Big Data Capabilities on Tourism Firms in Saudi Arabia

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Abstract

The Saudi Vision 2030 promotes digital transformation initiatives, which in turn drive the Big Data Analytics market. Tourism companies with their extensive digital presence, especially on social media, create and capture massive amounts of data. Big Data Analytics (BDA) is are methods that enable large-scale data sets, supporting people management decisions, and cost-effectiveness evaluation. The ability to leverage data effectively has become a key differentiator for firms seeking to enhance their decision-making processes, optimize operations, and drive innovation. To effectively leverage data, companies need a set of related capabilities such as Data-Driven (DD), Technology capability (TECH), Technical Skills (TKSL), Managerial Skills (MSKL), and Data-Driven Culture (DDC). However, the body of knowledge scares studies that assess the impact of these capabilities on firm performance, especially in the Saudi Tourism context. In response, redrawing on the RBT and social materialism theories, the current paper examines the impact of key big data capabilities—Data-Driven (DD), Technology (TECH), Technical Skills (TKSL), Managerial Skills (MSKL), and Data-Driven Culture (DDC)—on firm performance (FP) within Saudi Arabia's tourism sector. By analyzing how these factors influence the effectiveness and success of tourism organizations, the study aims to provide insights into the strategic role of possessing big data analytics capabilities in enhancing competitiveness and driving growth in this rapidly evolving industry. The current study employed a self-administered questionnaire. The variable measurements were derived from previously published studies. The researcher collected 695 responses: 220 were incomplete, and four responses were outliers. The valid responses are 471. The direct impact of DD and TECH on FP shows that DD and TECH capabilities do not directly enhance firm performance. The insignificant roles of DD and TECH may be attributed to the maturity level or implementation quality issues. The direct impact of TSKL, MSKL, and DDC on FP is statistically significant, suggesting that TSKL, MSKL, and DDC capabilities can directly enhance firm performance. Therefore, the corresponding hypotheses H3, H4, and H5 are accepted. While the hypotheses H1 and H2 related to DD and TECH are rejected. Therefore, organizations need to adopt a maturity model of various capabilities to guide the gradual development and integration of analytics capabilities. For future work, it is recommended to investigate contextual factors under which DD and TECH capabilities significantly impact FP, such as complementary capabilities, organizational culture, and analytics maturity.

***Keywords**: Data-Driven, Technology capabilities, Technical Skills, Managerial Skills, and Data-Driven Culture, firm performance, Saudi Arabia, Tourism*

1. Introduction

Big Data Analytics (BDA) are methods that enable large-scale data sets, supporting people management decisions, and cost-effectiveness evaluation (Sousa et al., 2019). BDA plays a crucial role in boosting organizational performance by transforming vast amounts of data into actionable insights (Mikalef et al., 2020). In today's competitive business environment, the ability to leverage data effectively has become a key differentiator for firms seeking to enhance their decision-making processes, optimize operations, and drive innovation. BDA enables organizations to identify trends, predict future outcomes, and respond swiftly to market changes, thereby improving efficiency and productivity (Sindarov et al., 2023) . From another perspective, BDA supports personalized customer experiences, enhances resource allocation, and fosters a culture of data-driven decision-making, all of which contribute to improved financial performance and competitive advantage as well. By integrating BDA into strategic frameworks, companies can unlock new growth opportunities, streamline processes, and achieve sustainable success in an increasingly data-centric world.

This paper examines the impact of key big data capabilities—Data-Driven (DD), Technology capabilities (TECH), Technical Skills (TKSL), Managerial Skills (MSKL), and Data-Driven Culture (DDC)—on firm performance (FP) within Saudi Arabia's tourism sector. By analyzing how these factors influence the effectiveness and success of tourism organizations, the study aims to provide insights into the strategic role of big data in enhancing competitiveness and driving growth in this rapidly evolving industry.

2. Problem Statement

The tourism sector of Saudi Arabia experienced significant growth from 2010 to 2019, at both the domestic and international levels. Though the sector experienced massive losses in 2020, The Total visitors' spend has dropped by approximately US$26 billion from 2019 by more than 60% (Saleh, 2025). In 2020, COVID-19 led to the loss of 62 million tourism jobs, leaving only 271 million employed globally. The sector's GDP contribution dropped by USD 4.9 trillion, a 50.4% decline, far exceeding the 3.3% drop in the global economy. In 2021, a modest recovery occurred, with tourism's GDP rising by USD 1 trillion (+21.7%) to USD 5.8 trillion. Its share of the global economy increased from 5.3% to 6.1% (WTTC, 2021). Any recession in the tourism sector causes negative impacts on economic growth (Bahrawi et al., 2021). Tourism companies need to boost their performance. This improvement is achievable through utilizing BDA.

BDA has the potential to help tourism companies improve their performance and quickly adapt to changing trends, allowing agility in response to evolving external factors and customer preferences (Sindarov et al., 2023). The Saudi Vision 2030 promotes digital transformation initiatives, which in turn drive the BDA market (Vision 2030, 2025). Tourism companies with their extensive digital presence, especially on social media, create and capture massive amounts of data, including transaction data, clickstream data, video data, and voice data. They are creating big data (BD) in massive amounts. Data-driven companies outperform competitors in profitability and productivity (McAfee & Brynjolfsson, 2012). However, simply having data does not mean they are used effectively. To leverage the benefits of these data in terms of better performance, companies need to invest in various technologies and embed them into business procedures (Akter et al., 2016; Mikalef et al., 2020) . Possessing various BDA capabilities allows companies to leverage the benefits of the collected data and have the potential to transform how companies manage their businesses (Popovič et al., 2018). In short, realizing improved performance depends less on having technology and more on being able to make the best use of it (Mikalef et al., 2020). Therefore, companies need to possess certain capabilities related to BDA. Big data analytics capabilities refer to the organizational capacity to gather and analyse data to derive valuable insights. This is achieved through the efficient development of various resources and capabilities related to data, technology, and talent, which is facilitated by organization-wide procedures, roles, and structures (Mikalef et al., 2020). For tourism companies to have effective BDA and hence improved performance, they need to establish and maintain different capabilities related to BDA. It can be capabilities related to the people, organization, data, technology, process, and even context (Mikalef et al., 2019)Figure 1.

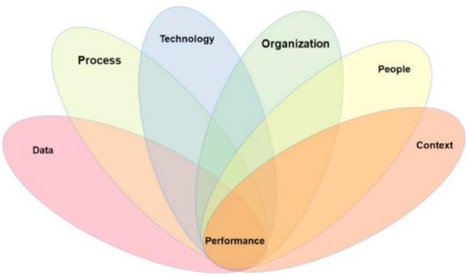

Fig. 1: Various Big Data analytic Capabilities Mikalf et al. (2019)

For hosting effective big data analytics, companies need to have, for example, Data-driven capability (DD), technology capabilities or (TECH), technical skills Capability (TSKL), Management skills Capability (MSKL), data-driven culture capability (DDC). There is not enough evidence that the presence of these capabilities positively influences firm performance. Thus, there is a significant knowledge gap in understanding how a particular resource can influence firm performance (FP).

The current study aims to examine the impacts of DD, TECH, TSKL, MSKL, and DDC on FP of tourism firms in Saudi Arabia.

3. Big Data Analytics Capabilities

Big data analytics entails multiple capabilities, including tangible resources (technology, data), human talents (management, technical skills), and intangible resources (data-driven culture). These resources are distinct and essential for building a comprehensive BDAC, and omitting any aspect can significantly alter its effectiveness (Mikalef et al., 2019, 2020; Gupta & George, 2016).

3.1 Tangible Resources

Tangible resources include key assets like data, technology, infrastructure, time, and investments (Gupta & George, 2016). In business, these are market-exchangeable resources such as financial assets (e.g., debt, stock) and physical assets (e.g., equipment, facilities)(Teece, 2014). Enterprises of similar size typically have easy access to tangible resources (Barney, 1991).

3.1.1 Data-Driven Capability (DD)

Data is an asset in the digital economy (Nolin, 2019). 'Data-driven' capability refers to the ease of access to enterprise-specific data generated by internal activities like inventory updates, accounting transactions, and sales (AlNuaimi et al., 2021). Various forms of data (e.g., texts, GPS, videos) are increasingly complex, requiring specialized technology for analysis (Nolin, 2019). BDAC isn't solely based on tangible technological resources but also requires technology-based resources like data (Mikalef et al., 2019). The economic significance of data is often described as "data as the new oil," "data as infrastructure," or "data as an asset." (Nolin, 2019). However, data monetization remains a challenge in the digital economy (Nolin, 2019). In 2016, the European Union's data economy was valued at roughly 300 billion euros, expected to grow to 739 billion euros by 2020 (Zech, 2017). Data can be categorized into internal (enterprise-specific data) and external data (data from external sources like the internet) (Birkel & Hartmann, 2020). Relying solely on internal data isn't enough to gain a competitive advantage; integrating both internal and external data streams is essential for developing BDAC(Bag et al., 2021; Mikalef et al., 2019). Generally, data can be public, private, data exhaust, community, and self-quantification data (George et al., 2014).

3.2 Technological capability (TECH)

Technological capability in BDA refers to the infrastructure's ability to support applications, hardware, data, and networks (Lee, 2020). Addressing the complexities of large, diverse, and evolving data requires creative solutions beyond traditional relational database management systems, which are suited for structured data like employee records and financial transactions. Organizations are now exploring alternatives and employing techniques like data warehousing to extract insights from enterprise-specific data (Arshad et al., 2023; Nnwobuike & Oghenekaro, 2021). Structured data management has been efficient with traditional methods, but about 80% of an organization's data is unstructured (Baviskar et al., 2021). Big data technology, such as Hadoop, which uses the Hadoop Distributed File System, has emerged to handle unstructured data efficiently. NoSQL databases like Cassandra, HBase, and MongoDB are key examples (Gupta & George, 2016). The prevalence of unstructured data, which makes up more than 90% of total data, further necessitates sophisticated big data techniques for meaningful insights (Su et al., 2022). Implementing BDA requires a robust technological framework that includes cloud computing, NoSQL databases, cognitive systems, and AI methods, ensuring compatibility with existing systems (AlNuaimi et al., 2021; Lnenicka & Komarkova, 2019).

3.3 Human Resources

Human resources encompass the expertise, knowledge, problem-solving skills, leadership, business acumen, and interpersonal connections within an organization (Gupta & George, 2016). BDA personnel capability is perceived as the professional skills and knowledge needed to perform BDA tasks, including a firm's ability to excel in coordinating business processes, reducing costs, and enhancing business intelligence (Lee, 2020). Prior research highlights the importance of both technical and management skills in BDA-related human resources (AlNuaimi et al., 2021; Gupta & George, 2016; Mikalef et al., 2019, 2020). This study identifies technical and management abilities as essential for human resources in big data environments, categorizing these competencies into two key areas: technical skills (TSKL) and managerial skills (MSKL).

3.3.1 Technical skills capability (TSKL)

Technical skills capability (TSKL) refers to the proficiency of personnel in BDA. BDA aims not only at technological advancements but also at developing personnel competencies (Bag et al., 2021). TSKL involves training employees in programming, analytics interpretation, and data management (Akter et al., 2016). The complexity of BDA requires personnel to understand and apply technology effectively (Jaouadi, 2022). Proficiency in big data and extracting insights is crucial for enterprises (McAfee & Brynjolfsson, 2012). TSKL is valuable for all organizations and requires new competencies beyond typical university curricula (Gupta & George, 2016). Building BDAC requires expertise in programming, data management, statistics, and machine learning, all closely linked to IT (McAfee et al., 2012). Analysts should possess technical knowledge, technology management skills, and business knowledge (Davenport & Patil, 2022). TSKL capability can be measured through training programs, hiring skilled employees, and assessing work experience in data analytics (AlNuaimi et al., 2021; Gupta & George, 2016; Jaouadi, 2022).

3.3.2 Managerial skills capability (MSKL)

Human resource competence in BDA includes technical proficiency, BDA technology management, business insight, and relational dynamics. MSKL assesses managers' familiarity with BDA, understanding of business requirements, and awareness of BDA-driven opportunities (Wamba et al., 2017). BDA planning, decision-making, coordination, and control are key management capabilities (Mikalef et al., 2019). Effective BDA managers must work well in teams, resolve conflicts, and communicate policies to support organizational efficiency and goals (Maurya & Sharma, 2017). MSKL is crucial for addressing business challenges via analytics, contributing to high performance (Mikalef et al., 2019, 2020). The use of MSKL in BDA is increasingly essential for decision-making and requires robust structural and procedural approaches and a data-driven culture (Lee, 2020). As BDA becomes integral to operations, senior management plays a crucial role in aligning strategies with organizational goals (Mikalef et al., 2019).

3.4 Intangible Resources

Intangible resources include elements like a data-driven culture (DDC) and corporate learning intensity. The focus in the current research is on DDC.

3.4.1 Data-driven Culture (DDC)

Organizational culture sets conduct standards for individuals within a company, shaping behaviors and fostering harmony, coherence, and innovation to enhance economic effectiveness (SHRM, 2021; Žukauskas et al., 2018). A strong culture leads to employees understanding expectations, believing responses are appropriate, and knowing they'll be recognized for upholding values (Bamidele, 2022). The DDC framework assesses how firms view data as an asset and the extent to which decisions are data-driven (Gupta & George, 2016; Mikalef et al., 2019). In the context of big data, DDC influences employee attitudes, collaboration, and the adoption of analytics procedures. It's crucial for successful big data applications, particularly in logistics supply chains (Dubey et al., 2019). DDC involves managing cultural and political complexities, aligning diverse talents, and embracing data analytics as key to decision-making (Bag et al., 2021). Success in BDAC depends on integrating structural practices with a strong DDC (McAfee et al., 2012).

3.5 Firm Performance (FP)

The concept of performance is extensively discussed in management, especially in strategic management, and is crucial for both academic researchers and professionals(P. Venkatraman & Levin, 2021). Despite existing guidelines for improving organizational performance, scholars continue to debate terminology, levels of analysis (individual, work-unit, organization), and conceptual frameworks for performance assessment (Ford & Schellenberg, 1982). Firm performance (FP) is frequently used as a dependent variable in research but lacks a universally accepted definition or measurement method. It is critical in strategic management as it measures the effectiveness and longevity of strategies and is often analyzed using financial and non-financial indicators such as market share, growth, profitability, and operational success(Buzzell et al., 1975; Zulganef et al., 2023). Firm performance can be defined in two primary ways: the achievement of economic objectives (Venkatraman & Ramanujam, 1986) and the efficient and effective use of resources to meet goals (Salamcı & Artar, 2021). Assessing firm performance helps determine how well pre-established objectives are met and identifies essential elements for long-term viability (Salamcı & Artar, 2021).

4. Research Model

Drawing on the RBT and social materialism theories, the current study proposes the research model shown in Fig. 1. The RBT describes how firms deploy resources and capabilities to obtain and maintain a competitive advantage (Barney, 1991; Wernerfelt, 1984). Socio-materialism conceptualizes the interrelatedness of the social and the material systems in organisations. The theory is based upon the premise that societal and technological represent two aspects that exist in a reciprocal relationship (Orlikowski, 2007).

We propose that BDACs involve a combination of resources: tangible (DD and TECH), human (TSKL and MSKL), and intangible resources (DDC), and each of these resources has an impact on firm performance. Figure 2 displays the research model that includes five hypotheses as follows:

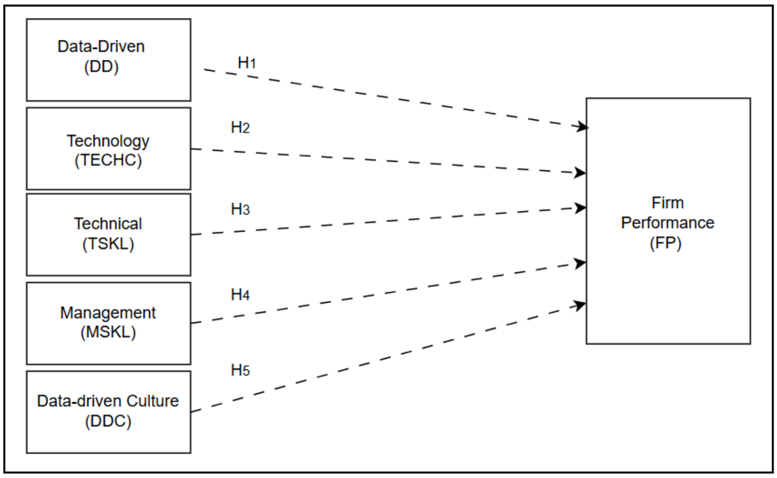

Fig. 2: Research Model

The first objective is to assess the impact of Data-Driven (DD) Capability on firm performance (FP). This objective aims to understand how the ability to base decisions on data, rather than intuition or experience alone, affects firm performance. By investigating this relationship, the study seeks to answer a critical question: How does possessing DD translate into improved firm performance in the tourism industry?

Developing an overall big data analytic capability involves leveraging resources related to data availability (Mikalef et al., 2019), data generation, data visualization, and data integration (Bag et al., 2021), with an emphasis on data quality, organizational elements, process management, people, systems, tools, technologies, and perceived organizational advantage (Surbakti et al., 2020).

Empirically, numerous studies highlight the critical role of DD in enhancing FP. In Saudi Arabia, Wided (2023) found that DD positively influences organizational resilience and strategic flexibility in SMEs. In the UAE, AlNuaimi et al. (2021) demonstrated the positive effect of data accessibility on environmental performance. In South Africa, Bag et al. (2021) established a significant correlation between data-related capabilities (such as data visualization, data integration management, and data generation) and decision-making in reverse logistics. Similarly, Mikalef et al. (2020) noted that in Norway, DD significantly impacts marketing capabilities through dynamic capabilities, enhancing competitive advantage.

Theoretically, this subobjective can be grounded in both RBT and Sociomaterialism theory. RBT posits that a firm's unique capabilities, derived from a combination of tangible and intangible resources, are essential for achieving competitive advantage (Barney, 1991). In this context, DD is seen as a crucial resource, enabling firms to effectively collect, process, and analyze vast amounts of data. This capability is not just about having the data but also about leveraging it to enhance decision-making and strategic initiatives. Sociomaterialism further underscores the impact of DD on FP by emphasizing that DD is not merely a technical asset but also a social construct involving human skills and managerial practices (Cooren, 2020). The effective utilization of DD necessitates a harmonious integration of technology, human expertise, and management practices. This integration ensures that data-driven insights are effectively translated into actionable strategies that drive firm performance. Based on the empirical and theoretical discussion, we hypothesize that:

H1: The data-driven capabilities of big data positively influence the performance of tourism companies in Saudi Arabia.

The second objective is to assess the impact of Big Data Technological Capability (TECH) on firm performance (FP) in tourism organizations in Saudi Arabia. This objective seeks to understand the extent to which the technology infrastructure (hardware and software), tools (such as advanced analytical platforms enabling data mining, predictive analytics, and real-time data processing), and systems (including efficient data management systems, security, and accessibility) contribute to the overall success and efficiency of tourism firms in Saudi Arabia. By assessing the impact of technological capabilities, organizations can understand how investments in technology translate into improved performance.

Empirically, numerous studies highlight the critical role of TECH capability in enhancing FP. In Taiwan, Lee (2020) found that implementing BD software and hardware infrastructure leads to significant improvements in financial performance indicators, such as cash flow, profitability, solvency, financial structure, and operating capability. This technological capacity enables BDA personnel to efficiently create, implement, and maintain essential system components. In Norway, Mikalef et al. (2020) found that technological capability significantly influences marketing capabilities, while Su et al. (2022) demonstrated the positive direct impact of technological big data capability on business performance in China.

Theoretically, RBT asserts that a firm's competitive advantage stems from its unique blend of tangible and intangible resources (Barney, 1991). Technological capabilities, including BD software and hardware infrastructure, are critical tangible resources that enhance a firm's ability to manage and utilize data effectively. This aligns with RBT's perspective that the strategic value of technological resources contributes to superior firm performance. Furthermore, Sociomaterialism enriches the relationship between TECH and FP by emphasizing the interconnectedness of technology, management, and human elements within an organization (Orlikowski, 2007). According to Sociomaterialism, TECH capability is not merely a technical asset but also a social construct involving human skills and managerial practices. The effective utilization of TECH capability requires a harmonious integration of technology, human expertise, and management practices. This integration ensures that technological aspects are effectively translated into actionable strategies that drive firm performance. Based on the empirical and theoretical discussion, we hypothesize that:

H2: The technological capabilities of BD positively influence the performance of tourism companies in Saudi Arabia.

The third objective is to assess the impact of Big Data Technical Capability (TSKL) on firm performance (FP) in tourism organizations in Saudi Arabia. This objective seeks to understand the extent to which these technical skills contribute to the overall success and efficiency of tourism firms in Saudi Arabia. By assessing the impact of technical capabilities, organizations can gain insights into how well their technical resources and expertise support business goals and drive performance improvements.

Empirically, numerous studies highlight the critical role of TSKL in enhancing FP. For example, in Saudi Arabia, Wided (2023) found that BDA significantly enhances the connection between strategic flexibility and organizational resilience in SMEs. Jaouadi (2022) established that improving staff capabilities contributes to enhanced organizational performance and fosters innovation in the supply chain. Cheng et al. (2022) demonstrated a positive influence of personnel expertise in BDA on supply chain performance and sustainable supply chain flexibility in India's manufacturing sector. AlNuaimi et al. (2021) emphasized the importance of human capabilities in e-business transformation, identifying them as crucial for developing and accessing business cases involving significant model changes and stakeholder collaboration. Mikalef et al. (2020) found that TSKL significantly influences marketing capabilities and competitive advantage, while Lee (2020) reported that the professional competency of BDA personnel positively impacts financial performance indicators, such as cash flow and profitability.

Theoretically, from the RBT perspective, TSKL represents a critical organizational resource that enhances a firm's ability to innovate and adapt to market changes. Firms equipped with skilled personnel can leverage technology more effectively, gaining a competitive edge and driving superior performance (Barney, 1991). Sociomaterialism further enriches this understanding by emphasizing the interplay between social practices and material resources (Orlikowski, 2007). It posits that TSKL does not exist in isolation but is developed through interactions among individuals, technologies, and organizational processes. This synergistic relationship between TSKL and FP highlights the importance of nurturing both technical competencies and supportive social dynamics to enhance overall organizational performance. Based on the empirical and theoretical discussion, we hypothesize that:

H3: The technical skills of BD (TSKL) positively influence the success of tourism companies in Saudi Arabia.

The fourth objective is to assess the impact of Big Data Management Capability (MSKL) on firm performance (FP) in tourism organizations in Saudi Arabia. This objective seeks to understand the extent to which managers' expertise in applying BDA contributes to the overall success and efficiency of tourism firms. By assessing the impact of management capabilities, organizations can gain insights into how effective management practices translate into improved performance.

Empirically, numerous studies highlight the critical role of MSKL in enhancing FP. For instance, in Saudi Arabia, Wided (2023) found a positive relationship between management capability and both organizational resilience and strategic flexibility in SMEs. In Norway, Mikalef et al. (2020) revealed that management skills significantly influence marketing capabilities, contributing to competitive advantage. In the UAE, AlNuaimi et al. (2021) emphasized the importance of human managerial capabilities in e-business transformation. In Taiwan, Lee (2020) found that professional competency in business development management positively impacts financial performance. Cheng et al. (2022) verified the impact of managerial competence on supply chain performance and sustainable supply chain flexibility.

Theoretically, the relationship between MSKL and FP can be robustly explained through the frameworks of RBT and Sociomaterialism. From the RBT perspective, MSKL represents a vital organizational resource that enhances a firm's ability to strategize, innovate, and respond to market dynamics. Managers equipped with advanced skills and knowledge can effectively allocate and utilize the firm's resources, leading to improved operational efficiencies and competitive advantage. Furthermore, Sociomaterialism enriches this analysis by highlighting the interplay between human managerial capabilities and material resources within the firm. It posits that MSKL is developed through the interaction of managers, technologies, and organizational processes. Effective management practices, combined with the appropriate technological tools, create a conducive environment for knowledge sharing and collaborative problem-solving. This interaction enables the firm to adapt to changes and seize opportunities, thereby enhancing overall performance. Based on the empirical and theoretical discussion, we hypothesize that:

H4: The managerial capability of big data (MSKL) positively influences the performance of tourism businesses in Saudi Arabia.

The fifth objective is to evaluate the impact of big data-driven culture (DDC) capability on firm performance in tourism organizations in Saudi Arabia. This objective seeks to determine whether, and to what extent, fostering a culture that emphasizes data-driven decision-making enhances the success and efficiency of these firms.

The primary goal of organizational culture is to promote harmony, coherence, employee engagement, and innovation, which contribute to overall economic effectiveness (Žukauskas et al., 2018). However, there is limited empirical research that highlights the critical role of data-driven culture in enhancing firm performance. For instance, in Norway, Mikalef et al. (2020) found that data-driven culture significantly influences marketing capabilities, enhancing competitive advantage through dynamic capabilities. In South Africa, Bag et al. (2020) demonstrated a positive correlation between data-driven culture and strategic and tactical reverse logistics decision-making. In Greece, Mikalef et al. (2019) observed that data-driven culture predicts firm performance. In the United States, Akter et al. (2016) emphasized the importance of a data-driven culture in the adoption of big data analytics and the improvement of organizational performance. McAfee and Brynjolfsson (2012) highlighted the importance of senior executives making data-driven decisions. Surbakti et al. (2020) noted that effective big data usage necessitates attention to organizational factors, including data-driven culture, process management, and data quality. Bamidele (2022) underscored the need for a culture grounded in widely embraced principles, supported by a resilient strategy and structure, to achieve success.

Theoretically, the relationship between data-driven culture and firm performance can be effectively analyzed through the lenses of RBT and Sociomaterialism. From the RBT perspective, data-driven culture is a valuable organizational resource that enhances a firm's capacity to leverage data for strategic decision-making, thereby driving competitive advantage (Mikalef et al., 2020). A strong data-driven culture enables firms to utilize their data assets more effectively, leading to improved marketing capabilities and overall performance (Mikalef et al., 2019). This cultural orientation towards data-driven decision-making ensures that firms can respond more swiftly and accurately to market changes, reinforcing their strategic flexibility and resilience (Bag et al., 2020). Sociomaterialism further enriches this understanding by emphasizing the interplay between social practices and material resources within the organization. It posits that a data-driven culture is mutually produced through the interaction of individuals, technologies, and organizational processes (Surbakti et al., 2020). This dynamic

interaction ensures that data is not only collected and analyzed but also effectively integrated into organizational workflows, resulting in sustainable performance improvements. Based on this empirical and theoretical discussion, we hypothesize that:
H5: The implementation of a data-driven culture within tourism businesses in Saudi Arabia positively influences corporate performance.

5. Methodology

The current study employed a questionnaire-based survey method due to the capability to investigate a wide range of factors simultaneously and to capture general trends and identify associations between variables within a sample (Straub & Gefen, 2004).The constructs and corresponding survey items in this questionnaire were derived from previously published studies (Akter et al., 2016; Gupta & George, 2016; Mikalef et al., 2020, 2020), with psychometric properties supporting their validity. All constructs and items were measured using a 5-point Likert scale. To check the clarity and suitability of the questions, three small-scale exploratory pilot tests for reviewing the questions were conducted with an expert and two academics. Then, in the pilot study, 30 random participants working in big tourism companies were invited through email. We collected additional feedback that helped in improving the questionnaire. For the main study, the researcher collected 695 responses: 220 were incomplete, and four responses were outliers. The valid responses are 471. The names and titles of senior IS executives at these firms were obtained from various sources, including corporate directories, personal contacts, and professional forums. Initial contact was made by phone to inform potential respondents about the study's purpose, confidentiality, and anonymity. Afterward, an email invitation to participate was sent, followed by two email reminders at three-week intervals. Respondents who had not completed the survey were re-contacted by phone to address any difficulties they encountered.

6. Results

The demographic analysis assists in contextualizing the findings. Table 1 shows that the sample has a higher proportion of males (almost 76 %), most respondents are well-educated, with 91 % holding a bachelor's, master's, or PhD. A significant portion of the respondents have moderate tenure spanning from one to five years. Almost half of the responses show practicing BDA for over five years, indicating a mature adoption. Though BDA adoption is prevalent across different company sizes, BDA is less predominant in small organizations.

Table 1: Demographic data descriptive analysis

Factor	Sample (471)	Proportion(%)
Gender		
Male	359	76.2
Female	111	23.6
Age		
Under 30	64	13.6
30 +	245	52.0
40 +	122	25.9
50 +	40	8.5
Education		
Bachelor/College	247	52.4
Master, PhD/higher	180	38.2
High School/ Diploma	44	9.3
Tenure		
one year or less	66	14.0
one to 5 years	235	49.9
5 years +	86	18.3
10 years +	84	17.8
Big Data Analytic Practice		
one year or less	98	20.8
1- 5 years	142	30.1
5 + years	227	48.2
Organization Type		
1- 9	38	8.1
10-49	165	35.0
50-249	202	42.9
250+	65	13.8

6.1 Measurement Model

The proposed model contains reflective constructions, namely, MSKL, TKSL, DDC, FP, and informative constructs, DD and TECH.

6.1.1 Reflective Constructs

Table 2: Assessment of reliability, convergent and discriminant validity of reflective constructs.

	DDC	FP	MSKL	TKSL
DDC	0.829			
FP	0.676 (0.767)	0.813		
MSKL	0.731 (0.812)	0.690 (0.769)	0.862	
TKSL	0.744 (0.840)	0.661 (0.751)	0.781 (0.868)	0.825
AVE	0.687	0.662	0.743	0.681
VIF	3.328	DV[a]	3.717	3.224
mean	4.21	4.18	4.14	4.15
ST.DEV	0.60	0.60	0.64	0.63
Cronbach's alpha	0.886	0.872	0.914	0.882
Composite reliability	0.916	0.907	0.935	0.914

a: FP is the dependent variable

Reflective constructs are those where the latent variable is presumed to cause the observed indicators (Mikalef et al., 2020). MSKL, TSKL, DDC, and FP are reflective constructs (Figure 3. Confirmatory Factor Analysis (CFA) validates the measurement model through reliability and validity tests. All the constructs show high levels of internal consistency and reliability. The average variance extracted (AVE) values verify the convergent validity of MSKL, TSKL, DDC, and FP (=> 0.5). The indicators within each construct are strongly related and measure a coherent concept. Discriminant validity refers to the extent to which a construct is separate and distinguishable from other constructs or measures that may share similar concepts. It ensures that the construct does not overlap with another construct Hair et al., 2021; Ramayah, Cheah, Chuah, Ting, & Memon, 2018). There are various methods to assess discriminant validity. In the current study, discriminant validity was established through testing two measures. First, the Fornell–Larcker criterion checks each construct's AVE square root to verify that it is greater than its highest correlation with any other construct (square root of AVE >the correlations between that construct and all other constructs(. This ensures that a construct shares more variance with its indicators than with other constructs. As displayed in Table 2, the diagonal values represent the square roots of the AVE for each construct, while the Off-diagonal elements represent the correlations between the constructs. Furthermore, Henseler et al. (2015) state that the Heterotrait-Monotrait ratio (HTMT) is a better assessment indicator of discriminant validity. HTM ratios greater than 0.9 suggest a lack of sufficient differentiation between the constructs. the HTMT values for various constructs are below 0.9 (Table 2 off-diagonal values between brackets), indicating that each two constructs is distinct and separate from each other. Both the Fornell-Larcker criterion and HTMT confirm the discriminant validity, where each construct in the model is distinct and well-defined.

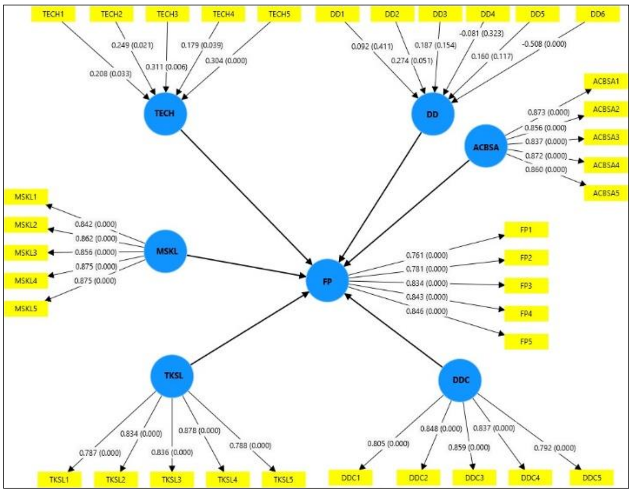

Fig. 3: Measurement Model, Weights and Outer loadings

6.1.2 Formative Constructs

Formative indicators cause the construct rather than reflect it. The latent variable is formed by its indicators. Changes in the indicators lead to changes in the latent variable. Therefore, the traditional reliability and validity tests used for reflective constructs are not appropriate for formative constructs. Alternatively, weights, significance, and collinearity were employed to assess the quality of the formative constructs DD and TECH. Remarkably, the DD construct is formed by the organization's various capabilities related to accessing, integrating, and utilizing different types of data for analysis. TECH construct is formed by the organization's adoption and utilization of various advanced technologies for big data analytics

Bootstrapping helps assess the statistical significance of the outer weights of the formative indicators. A bootstrapping analysis of 5000 samples was performed. Setting enough subsamples, typically 5,000 or more, is essential to ensure reliable estimates. According to Table 3, there are statistically insignificant indicators in DD and TECH. According to (Cenfetelli & Bassellier, 2009; Mikalef et al., 2020), formative constructs are likely to have some indicators with nonsignificant weights. They suggest that a nonsignificant indicator should be kept, provided that the researchers can justify its importance. Additionally, when the weights are insignificant, it is recommended to look at the outer loadings. A similar approach is followed by (Gupta & George, 2016; Mikalef et al., 2020) in their operationalization of BDAC. As displayed in Table 3, since DD6 has a significant weight, it will be kept. DD2 has a borderline significance with an outer loading of 0.848 (> 0.70(, so the decision is to keep it. Similarly, DD1, DD3, and DD5 each have insignificant weights, but the decision is to keep them due to their substantial loadings. Only DD4 shows moderate loading of 0.478, but it still contributes in a distinguished manner to the DD construct, and the decision is to keep it. The Data construct is proposed as an aggregate of six items, where each captures a different data-related capability; therefore, it is critical to include all the indicators in the model as they make a distinct contribution.

Table 3: Formative Constructs reliability and validity

Construct	Indicator	Weight	Significance (p- p-value)	VIF	Outer loadings
DD	DD1	0.092	0.411	2.120	0.729
	DD2	0.274	0.051	3.141	0.848
	DD3	0.187	0.154	2.839	0.810
	DD4	-0.081	0.322	1.466	0.478
	DD5	0.161	0.117	2.128	0.783
	DD6	-0.508	0.000	2.124	-0.909
TECH	TECH1	0.208	0.033	2.431	0.819
	TECH2	0.249	0.021	2.419	0.833
	TECH3	0.312	0.006	2.598	0.860
	TECH4	0.179	0.039	1.855	0.758
	TECH5	0.304	0.000	2.653	0.744

P-values at 95% confidence interval

6.2 Structural Model

After making sure of the reliability and validity of the measurement modelling, as well as the absence of multicollinearity issues in the variables, structural modelling is employed to test the proposed hypothesis. The overall measurement model demonstrates a good fit for the structural model's evaluation and estimation. The structural research model assigns connections among research constructs.

6.2.1 Path Coefficients, explanatory and predictive powers

The absolute value of the path coefficient refers to the strength of the relationship: 0.10 refers to a small effect, 0.30 refers to a medium effect, and 0.50 and above refer to a large effect (Hair et al., 2021). The Sign indicates the direction of the relationship. Figure 3 depicts the standardized path coefficients at the 5 % significance level ($p < 0.05$).

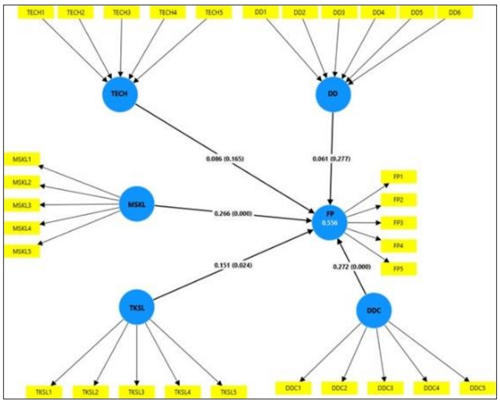

Fig. 3: Structural Model

The relationships between DD, TECH, and FP have a very weak and insignificant path coefficient (0.061, 0.086, P> 0.05). Similarly, the relationship between TECH and FP has a very. Therefore, there is insufficient evidence to suggest that data-driven or technological capabilities directly impact firm performance. On the other side, the relationship between DDC, MSKL, and TSKL has a moderate positive and significant path coefficient (0.272, 0.266, 0.151, P=000). This suggests that there is a piece of evidence to suggest that technical skills, Managerial skills, and data-driven culture capabilities are associated with firm performance.

As Table 3 displays, the explanatory power R^2 value of 0.556 shows that the model explains a significant portion (55.6%) of the variance in Firm Performance, indicating strong explanatory power. The adjusted R^2 value of 0.552confirms that the model remains efficient and accurate when accounting for the number of predictors. Table 3 also illustrates that the Predictive power Q2 is 0.537. It was tested based on the blindfolding procedure. The value highlights the model's strong predictive capability, suggesting that it can effectively predict new, or out-of-sample data related to Firm Performance.

Table Error! No text of specified style in document.Explanatory and Predictive Power

Relationship	f^2
DD	0.003
DDC	0.061
MSKL	0.045
TECH	0.006
TKSL	0.016
R^2	0.556
R^2 adjusted	0.552
Q^2	0.537

The dependent variable: FP

The interpretation of the f2 value (Table 3) helps to understand which factors play a more significant role in influencing firm performance within the model. The f2 value of 0.003 and 0.006 indicates a negligible effect size of DD and TECH on FP. They have a very minimal contribution to the variance explained in FP. While the small effect sizes of DDC, TSKL, and MSKL suggest these factors are important, they may need to be considered alongside other variables or potential mediators/moderators to fully understand their impact on firm performance.

6.2.2 Hypothesis Testing

Since the overall fit and validity of the SEM have been established, the hypothesized theoretical relationships can be tested (Table 4).

H1: DD capability has a positive impact on the firm performance in tourism organizations in Saudi Arabia

H2: TECH has a positive impact on the firm performance in tourism organizations in Saudi Arabia

The direct impact of DD on FP (path coefficient=0.06, p=0.277) (Figure 2) suggests that DD capability does not directly enhance firm performance. Similarly, the direct impact of TECH on FP (path coefficient=0.086, p=0.165) (Figure 2) suggests that TECH capability does not directly enhance firm performance. The insignificant roles of DD and TECH may be attributed to the maturity level or implementation quality issues, where the quality of data-driven initiatives is not fully utilized. The insignificant roles of DD may be attributed to the maturity level, where the organizations in the sample may not have reached a sufficient maturity level in their data-driven practices. It might be attributed to the implementation quality issues.

H3: TSKL has a positive impact on the firm performance in tourism organizations in Saudi Arabia.

H4: MSKL has a positive impact on the firm performance in tourism organizations in Saudi Arabia.

H5: DDC capability has a positive impact on the firm performance in tourism organizations in Saudi Arabia.

The direct impact of TSKL, MSKL, and DDC on FP (0.151, 0.266, and 0.272, respectively) (Figure 2) is statistically significant and suggests that TSKL, MSKL, and DDC capabilities can directly enhance firm performance. Therefore, H3, H4, H5 are accepted. While the hypotheses H1 and H2 related to DD and TECH are rejected.

Table 4: The Hypothesis Testing

Hypothesis	Relationship		Direct effect (M)	Sig.
H1	DD -> FP	Rejected	0.061	0.277
H2	TECH -> FP	Rejected	0.086	0.165
H3	MSKL -> FP	Accepted	0.266	0.000*
H4	TKSL -> FP	Accepted	0.151	0.024*
H5	DDC-> FP	Accepted	0.272	0.000*

7. Discussion

Contrary to the current study's results, the importance of DD and TECH in supporting performance in various contexts has been investigated and observed by various empirical studies from various countries. In Saudi Arabia, Wided (2023) found that the presence of infrastructure capability, specifically comprising data and technological resources, has a beneficial influence on the organizational resilience and strategic flexibility of SMEs. Inside the United Arab Emirates (UAE), AlNuaimi et al. (2021) have affirmed the influence of data accessibility on environmental performance. In South Africa, Bag et al. (2021) discovered a significant correlation between various data-related capabilities and the decision-making process. In Norway, Mikalef et al. (2020) affirmed that data-related and technological capabilities have a significant influence on marketing capabilities. In Taiwan, Lee (2020) showed that the implementation of BD software and hardware infrastructure resulted in notable improvements in several financial performance indicators. In China, Su et al. (2022) found that the TECH exhibits a beneficial direct impact on business performance.

The insignificant effects of Data-Driven Capability (DD) and Technological Capability (TECH) on firm performance may be attributed to several underlying barriers. One key factor is the limited maturity level of data analytics within many tourism firms in Saudi Arabia. Organizations may lack the necessary infrastructure, such as advanced data management systems or cloud-based platforms, which are essential to fully operationalize big data initiatives (Gupta & George, 2016; Mikalef et al., 2020). The lack of infrastructure and resources, the shortage of skilled personnel, the absence of data privacy regulations, the digital divide, and the high cost of implementing new technologies are known for developing countries (Barsha & Munshi, 2023). Additionally, resistance to data-driven decision-making remains a challenge. In firms with traditional leadership, family, or hierarchical structures (Ajao & Ejokehuma, 2021; Bazhair & Alshareef, 2022)Employees and managers may rely more on intuition than on data insights (McAfee & Brynjolfsson, 2012). Another critical barrier is poor implementation quality. The effectiveness of DD and TECH capabilities may be dependent on the quality of their implementation (Hirschlein et al, 2022). Having access to technology or data does not guarantee impact unless properly aligned with organizational goals and processes (Akter et al., 2016; Sindarov et al., 2023). In some cases, firms may adopt fragmented or outdated systems that are incompatible with newer tools, leading to inefficiencies. Poor implementation or immature technological practices might result in a negligible impact on firm performance. Additionally, DD and TECH capabilities may need to be effectively integrated with other organizational capabilities (e.g., managerial skills, data-driven culture) to have a meaningful impact on performance (Mikalef et al., 2020). This finding suggests that isolated investments in data or technology are unlikely to yield value unless supported by complementary capabilities and an enabling environment.

In line with the current results, numerous empirical studies conducted in various countries have consistently demonstrated the favourable influence of various big data-related capabilities such as TSKL, MSKL, and DDC on firm performance. In Saudi Arabia, Wided (2023) has observed that technical staff capability and managerial capability have a significant role in stimulating and strengthening the connection between strategic flexibility and organizational resilience in SMEs. In Saudi Arabia, Jaouadi (2022) established that enhancing the capabilities of staff members contributes to improved organizational performance and fosters innovation within the supply chain domain. Mikalef et al. (2020) revealed in Norway that Management Skills capability significantly influences marketing capabilities and hence contributes to competitive advantage. In the UAE, AlNuaimi et al. (2021) emphasized the importance of human managerial capabilities, especially handling uncertain information, and effectively collaborating with all stakeholders, in e-business transformation. In Jordan, specifically in the telecommunications sector, Aburub et al. (2024) observed a significant impact of big data analytics capabilities on decision making. In Taiwan, Lee (2020) found that professional competency in business development management positively impacts financial performance. Cheng et al. (2022) verified the impact of managerial competence and personnel expertise skills and their influence on supply chain performance. In China, Wu and Zhang (2021) found that various big data capabilities have a positive impact on firm performance, mediated by sensing, seizing, and reconfiguring. In India and China, Behl (2020) found that big data analytics capabilities have a significant positive impact on both firm performance and the competitive advantage of tech startups.

Regarding data-driven culture, organizational culture in general aims to cultivate a sense of harmony and coherence inside the company, while also catalyzing employee excitement and innovation. This, in turn, contributes to the overall economic effectiveness of the organization (Žukauskas et al., 2018). However, there is a scarcity of research that specifically examines the DDC on performance. Though the findings ensure the role of DDC in enhancing the performance. Mikalef et al. (2020) ensured the positive impact of DDC on marketing capabilities. Bag et al. (2020) demonstrated a positive correlation between DDC and strategic and tactical reverse logistics decision-making in South Africa. In the Greek context, Mikalef et al. (2019) observed that DDC serves as a predictor of firm performance. In the United States, Akter et al. (2016) emphasized the significance of DDC in improving organizational performance.

The result aligns with what the RBT posits. The positive impacts of TSKL, MSKL, and DDC on FP emphasize that firms can gain a competitive edge by leveraging technical and managerial skills as well as an overall data-driven culture as valuable, rare, inimitable, and non-substitutable resources. This supports the notion that these capabilities are a critical resource that can drive superior firm performance. The study extends the sociomaterialism theory by demonstrating how TSKL, MSKL, and DDC integrate with organizational processes and culture to enhance performance. The significant roles of managerial, technical skills, and data-driven culture capabilities highlight the interplay between technology and human factors in achieving effective BDA implementation. This underscores the importance of considering both technological and social dimensions in understanding how capabilities and resources related to BDA contribute to firm performance.

8. Recommendation, Future Work, and Limitations

Based on the current results, the author recommends a type of ensuring a type of integration between various capabilities. Focus on aligning DD and tech capabilities with organizational processes and strategic objectives. The author strongly encourages entrepreneurs to invest in managerial skills, technical skills, and fostering a data-driven culture through training and development. It is also essential for organizations to adopt a maturity model of various capabilities to guide the gradual development and integration of analytics capabilities. For future work, it is recommended to investigate contextual factors under which DD and TECH capabilities significantly impact FP, such as complementary capabilities, organizational culture, and analytics maturity. Scholars may resort to conducting longitudinal studies to assess the long-term effects of various capabilities on FP. Though the valuable results of the current study, it comes with several limitations. Recognizing limitations helps in better interpreting the results and underscores the areas where further research is needed. First, in terms of sample size and scope, the diverse range of tourism companies in the study may not fully capture variability across regions and enterprise types, limiting the generalizability of findings. Second, the study's cross-sectional design captures relationships at a single point in time, limiting insights into how these relationships evolve. Third, the study focused mainly on specific big data capabilities, leaving out factors like organizational structure, leadership styles, and market conditions. Finally, reliance on quantitative methods may overlook deeper insights into how and why each capability impacts firm performance, which qualitative approaches could provide. Accordingly, future research should use a mixed-methods approach. Quantitative methods can show patterns between BDA capabilities and performance. Qualitative methods, like interviews or case studies, can explore deeper issues. These include culture, infrastructure, leadership, and employee resistance. Combining both methods offers a full picture. It helps explain why BDA works in some settings but not others. This is especially useful in the Saudi tourism sector, where local context matters.

9. Conclusion

The current research is based on a quantitative approach and analyzes 471 questionnaires from top and middle management employees working in different Saudi tourism companies. The results highlight the significant positive impact of three big data analytic capabilities, namely, technical and managerial skills, as well as data-driven culture capabilities, on FP. However, the study also found that data-driven and technology capabilities did not show a significant impact on FP in the current context. The insignificant roles of DD and TECH reflect the possibility that the surveyed organizations may not have reached a sufficient maturity level in their data-driven or technological practices. It may be due to implementation quality issues. Therefore, DD and TECH capabilities may need to be effectively integrated with other organizational capabilities (e.g., managerial skills, data-driven culture) to have a meaningful impact on performance. From the academic perspective, the current results are limited due to the reliance on a quantitative method that may overlook deeper insights into how and why each capability impacts firm performance, which qualitative approaches could provide.

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