Mobilising Big Data Analytics Capabilities to Improve Performance of Tourism Supply Chains: The Moderating Role of Dynamic Capabilities

Abstract

Purpose: With the emergence of big data analytics and the importance of analytics-driven decisions, the travel industry is swiftly jumping on and adopting the bandwagon. However, research in this domain is limited. Accordingly, the present research seeks to understand how Big Data Analytics Capabilities (BDAC) add value to Tourism Supply Chains (TSCs) and can Dynamic Capabilities (DC) improve the triple bottom line.

Design/methodology/approach: Data from 218 valid responses were collected from different Indian tourism industry units. Confirmatory factor analysis (CFA) was applied to confirm the constructs, followed by partial least squares structural equation modelling (PLS-SEM) to check the mediating effect of dynamic capabilities (DC) on TSCs performance.

Findings: The findings show that BDAC significantly influences the performance of TSCs and that DC plays a critical role in strengthening the impact of BDAC on TSCs' economic performance. These results corroborate that DC plays a key moderating role.

Research limitations/implications: This study contributes significantly to the tourism sector in India, where tourism is a key contributor to the country's gross domestic product. Theoretically, this study contributes to the resource-based view (RBV) and practically encourages professionals in the tourism sector to promote the use of BDAC to enhance the performance of TSCs.

Originality: The originality of the study is that it has tried to comprehend the moderating role of dynamic capabilities which impact BDAC to improve TSC performance.

Keywords: Big data analytics capability; tourism supply chains; dynamic capabilities; resource-based view; firm performance

1. Introduction

Travel and tourism are the largest industries in the world and the largest creators of employment across the economy (Wut et al., 2021; Wieczorek-Kosmala, 2022). The tourism industry contributes progressively to a country's economic growth through various channels and promotes technology and innovation (Ajmal et al., 2022). Alford and Jones (2020) stress how adopting digital and technology-based marketing in tourism promoted entrepreneurship in England.

The India Brand Equity Foundation (2019) stated in its report that the "*tourism sector created 8.1 per cent of total employment in the country*". As BDAC can lead to job creation like data scientists, data analysts, and data engineers, these roles can further help in tourism marketing, sales, and customer service. BDAC can help tourism companies to improve their operational efficiency, personalize their services, and attract more customers. Therefore, an increase in employability is a crucial component of economic viability in tourism supply chain performance. Tourism has the potential to positively impact the lives of local communities and to support cultural heritage. Sustainability can ensure that the benefits of tourism are distributed fairly and that local communities have a voice in decision-making processes, and that the socio-cultural legitimacy of host communities is sustained. For this purpose, the tourism industry must continuously look for new technologies, such as big data analytics capabilities (BDAC), to gain a clear insight into how it can be better developed and promoted (Gkoumas, 2019). Big data has emerged as a prominent solution for efficiently handling the supply chain (Centobelli & Ndou, 2019). This study focuses on how BDAC can improve the performance of tourism Supply Chains (TSCs). TSCs can be explained as a group of varied tourism activities, extending from offering flights, transportation, accommodation, hospitality, travel agencies, and tourist shops to satisfying tourist requirements in the tourism area (Fong et al., 2021).

In this context, BDAC aids in enhancing coordination and cooperation between different entities, such as hotels, travel agencies, restaurants, and airlines, to ensure the sustainability of operations. Sustainability principles refer to the environmental, economic, and socio-cultural aspects of tourism development (Sustainable Development | UNWTO, n.d.). Tourism has a significant impact on the environment, and adopting viable practices can help in minimizing negative impacts and preserve the environment for future generations. Negative impacts on a destination include economic leakage, damage to the natural environment, and overcrowding. Sustainable tourism can support the long-term economic viability of destinations by creating jobs, generating income, and attracting investment (Madanaguli et al., 2022). Furthermore, BDAC has led to the gathering of electronic customer feedback data at major tourist destinations, which helps tourism agencies maintain supply chains (Mandal, 2018). BDAC has also proven to provide remarkable support for airlines by increasing information handling and streamlining their supplier selection process (Belhadi et al., 2021). BDAC in the hotel sector helps adjust dynamic pricing and maintains proper revenue management (Melis & Piga, 2017). It also helps provide guest data and travel agent details (Lv et al., 2021) to hotel managers. Further, it provides them with timely information about seasonal fluctuations, delivery time, and deadlines between inventory to be maintained, orders, and available products (Go et al., 2020; Lv et al., 2021), generating viable business conditions for hotels (de Bastos, 2022). BDAC helps analyse copious amounts of information and evidence collected from various origins in many forms and types (Chai et al., 2021).

The supply chain in the service industry is more complicated than that of manufacturing firms because of operational diversity and variation in partner involvement (Gunasekaran & Spalanzani, 2012). In this era of technological advancement, it is difficult for tourism companies to identify dynamic changes in consumer preferences. Thus, companies are developing strategies and competencies related to sensing, learning, integrating, coordinating, and reconfiguring to improve their performance (Mikalef et al., 2019). This study also emphasises the moderating impact of dynamic capabilities (DC) between BDAC and TSCs performance.

Modern technologies can remove intermediaries from the tourism sector's supply chain, assisting travellers by making their trips more efficient and affordable (Rashideh, 2020). Big data can function as a relationship and trust-building instrument between customers and tourism firms (Line et al., 2020). Therefore, all these forces reform the demand, supply, competitive environment, and consumers' decision-making. Online services transfer power from suppliers to customers, especially in tourism (Akter et al., 2020).

BDAC is an emerging concept through which organisations can process large amounts of data and information more conveniently and understandably. Hence, big data helps companies understand their prospective customers, consumption habits, needs, and demands and can better understand their profile. In addition, digitalisation helps the tourism industry secure more information about their future clients in advance (Perelygina et al., 2022). With this background, identify a gap by reviewing the previous studies as mentioned in Table 1. The main purpose of this study is to address these key issues in TSCs. First, how can BDAC add value to the TSCs? Second, can DC improve the triple bottom-line variables in TSCs? Thus, to answer the research questions, the following objectives were formulated:

i. To explore the key factors of BDAC that significantly affect the performance of TSCs, and
ii. To analyse DC's role in strengthening BDAC's effect on TSCs performance.

This research shows that integrating all available organisational resources with BDAC assists in achieving a feasible, manageable, and controllable supply chain. This practice allows tourism companies across the chain to work together and develop dynamic capabilities and profitability. Furthermore, this study confirms the moderating effect of dynamic capabilities on the relationship between BDAC and economic performance. This shows that dynamic supply chain capabilities can improve sustainable competitive advantages in the tourism industry.

Researchers and practitioners are paying more attention to this area (Babu et al., 2018). A vast amount of research has been conducted on the tourism supply chain (Babu et al., 2018; Mandal & Dubey, 2020), but very few extensive empirical tests and theoretical developments exist to understand the impact of BDAC on firm performance (Centobelli & Ndou, 2019). This is the first research gap that the current study seeks to address. While there are several empirical studies on the importance of risk management and mitigating risks in supply chains (Ukpabi & Karjaluoto, 2017), there is very limited research on the role of dynamic capabilities and their impact on firm performance (Stekelorum et al., 2022), thereby underpinning the second research gap. Previous studies have also highlighted the paucity of studies in the context of India in the tourism sector (Table 1).

Table 1. Literature review of recent studies on supply chain and big data

Author	Sample size	Country	Sector	Methodology	Main Findings
Chowdhury et al. (2019)	274	Bangladesh	Apparel	Hayes Process and SEM	The results suggest that supply chain resilience, i.e., flexibility, redundancy, visibility, and dimension of collaboration, has a significant positive relationship with the performance of the SC.
El Baz & Ruel (2020)	470	France	Manufacturing firms	SEM	The results show that the mediating role of supply chain risk management practices plays a prominent role in promoting the resilience and reliability of the SC.
Mandal & Dubey, (2020)	302	India	Hotels and tour companies	SEM	The study finds that tourism IT adoption is a prominent resource at the company level, which can improve the dynamic capabilities of TSCs agility and tourism supply chain resilience for the tourism industry.
Shibin et al. (2020)	205	India	Auto components industry	Variance-based SEM	This study states that by building reliable supply chain connectivity and information-sharing systems, organisations can effectively integrate the SC and help with sustainable performance.
Arora et al. (2020)	317	USA	Food and beverage, consumer products, etc.	PLS-SEM	The results support that supply base size plays an important role in determining the link between strategic sustainable purchasing and organisational performance.

Agyabeng-Mensah et al. (2020)	139	Ghana	Manufacturers of plastics, textiles, food, etc.	PLS-SEM	The findings reveal that the adoption of internal green supply chain practices can have a negative impact on the company's financial performance.
Kitchot et al. (2020)	203	Thailand	Small- and medium-sized firms (SME)	SEM	The findings recommend that SEM cannot enhance SME performance if it is executed without efficacious human resource management practices.
Dovbischuk (2022)	113	USA and Europe	Logistic Service Providers	Factor analysis	Applying dynamic capabilities is useful for improving logistics service quality and performance of the company.
Sharma et al. (2022)	263	UK	Retail (grocery) stores.'	SEM	The study shows that SC traceability and information sharing positively impact visibility. Moreover, visibility positively affects the adoption of sustainable practices and affects SC performance.

*Source: Authors own work

This study proposes and validates a model that illuminates the role of BDAC as the firm's capability to collect and evaluate data in the direction of coherent understanding of efficiently organising and distributing its tangible, intangible, and human skills (Mikalef et al., 2018; Bag et al., 2021). Moreover, this study examines the moderating effect of DC on the path connecting BDAC and three bottom-line variables of TSCs: social performance, economic performance, and environmental performance of the tourism supply chain. Finally, this study contributes significantly to the tourism sector in India, where tourism is a key contributor to the country's GDP.

The rest of the paper is as follows: the theoretical framework is presented in Section 2, and the research hypotheses are formulated in Section 3. Section 4 describes the research methodology, and Section 5 presents the statistical analyses. In Section 6, the discussion and implications are presented. Finally, the conclusions of the study are provided in Section 7.

2. Theoretical Framework Development

The tourism industry has also grown significantly worldwide in the service sector. The advanced development in the tourism sector is vital for companies to attain a competitive advantage and meet ever-increasing customer expectations. The tourism industry developed TSCs to balance supply chain capabilities and tourists' requirements (Zhang et al., 2009). Tourism Supply Chains (TSCs) can be explained as a tourism organisation network engaged in multiple activities, from providing a whole range of components of tourism products/services, such as transportation companies, accommodation at the tourist reception desk, attractions like amusement parks, museums and season end sale of tourism products in the tourism area (Zhang et al., 2009). Tapper and Font (2004) define TSCs as a chain consisting of suppliers for varied products and services coordinating together to deliver tourism-related products and services to consumers.

TSCs comprise local operators, tour operators, customers, and other supporting members who transfer the required resources (Baltacioglu et al., 2007). TSC works through business-to-business connections and can be implemented for performance improvements i.e., financial performance, by improving the business operations of each supplier in the supply chain. TSCs consist of many components such as accommodation, transport and excursions, bars and restaurants, crafts, food production, waste disposal, and infrastructure that supports tourism. Each component in the tourism supply chain is dependent on the others for success and profitability. For example, tourists expect all the above components when buying holidays, regardless of whether the suppliers of these components are directly contracted by a tour operator or not. Customer satisfaction depends on performance at all the links in the TSCs.

Big data analytics (BDA) intends to create economic value from huge data of a different variety by facilitating high-speed trapping, discovery, and evaluation (Mikalef et al., 2018). Few studies have demonstrated a significant relationship between the application of BDA and the firm's performance (Gupta and George, 2016; Wamba et al., 2017). When applied to the tourism sector, the key assumption reinforcing the concept of BDAC is that firm resources can be easily duplicated (Mandal, 2018). However, unique and firm-specific capabilities cannot be replicated and collected in markets. Hence, BDAC can be a basis for a sustained competitive advantage (Wamba et al., 2017).

2.1 Resource-Based View

The resource-based view (RBV) was established because companies with different resources can gain a competitive edge (Barney, 1991). According to this theory, resources, and capabilities comprise tangible and intangible assets, managerial skills, organisational processes and routines, and the information and knowledge a firm administers. The fundamentals of the theory are based on the resources and a firm's capability to control the analysis structure, which can be used to enhance firms' competitive advantage (Barney & Clark, 2007).

RBV theory is centred on two assumptions: the creation of distinctive resources to carry out specific functions, also known as resource heterogeneity, and synergistic advantages from the distinctive resources, that is, resource immobility, to maintain its feasibility (Barney & Hesterly, 2012). Hence, resources and capabilities are integral to the RBV (Amit & Schoemaker, 1993). Croes et al. (2021) highlight the impact of the RBV model on firm performance; the types of organisational resources and incentives for executives need to be altered following the various phases of the firm.

2.2 Dynamic Capabilities View

DC is the skill to integrate, develop, and reconstruct internal and external capabilities to respond to rapidly transforming business environments (Teece et al., 1997). Thus, Dynamic Capabilities View (DCV) is the firm's ability to form, broaden, and change its resources to accomplish the required objective (Ambrosini et al., 2009). Owing to increasing business environment uncertainties (Pal et al., 2018), more firms depend on DC to create effective uncertainty management strategies (Sun et al., 2018). Wright et al. (2001) proposed that resources, DC, and information are closely interconnected. Besides, firms use specific methods and change their resource bases to attain competitive advantage (Mandal, 2018). Further, it is also suggested that the learning capacity and the capability to change will be expected to be among the most crucial capabilities a firm can possess (Hidalgo-Peñate et al., 2019). Therefore, it can be asserted that RBV emphasises choosing the appropriate resources, while DC emphasises resource development and renovation (Hitt et al., 2016).

3. Hypotheses Development

Mandal (2018) states that DC helps tourism firms adjust to environmental changes and enhances tourism firm performance. This study supports this framework using the RBV (Barney, 1991) and DCV concepts (Wilden et al., 2013). Following the literature, the impact of a resource-based perspective on a firm’s dynamic capabilities can influence its overall performance (Song et al., 2021). This has led to the dynamic capabilities of firms becoming one of the main bases for sustainable competitive advantages.

According to Wang et al. (2016), DC helps build sustainable firm performance by focusing on improved coordination among various actors in the tourism industry. Mandal (2018) argues that the relationship between BDAC and tourism firms’ performance is not well established. Therefore, it can be argued that a tourism firm's DC role can act as a moderating construct between BDAC resources and tourism firm performance. Researchers should also explore other theoretical frameworks, such as RBV, to establish robust big data-driven TSCs.

This study uses a three-stage model to illustrate the association between firm resources, BDAC, and firm performance. The framework is designed to examine the role of DC in enhancing supply chain capabilities and their overall effect on performance. In assessing firm resources, the intensity of DC in the present use stage and directions for the future implementation of BDAC were investigated. Reliant on the present utilisation of BDAC implementation, our goal is to unveil the transformational effect of BDAC on a firm's total performance. Within the framework of this model, the extent of BDAC's (in the presence of DC) impact on overall firm performance is explored. The authors adopted Gupta and George's (2016) definition of resources. They considered seven types of resources broadly classified into three categories: tangible, human, and intangible resources. Data, technology, and other basic resources comprise tangible resources. They also considered two aspects of human resources: managerial and technical big data skills. A data-driven culture and the intensity of organisational learning are crucial intangible resources required to develop BDAC. Additionally, the authors emphasise the importance of BDAC in tourism firms.

3.1 Tangible Resources and Big Data Analytics Capabilities

Organisational, human, and physical capital are collectively known as tangible resources (TR). These resources (concerning big data) comprise internal organisational setups, data analysts, and hardware (Braganza et al., 2017). Consistent with Dubey et al. (2019a) and prior IT capability studies, it can be argued that TR considerably influences BDAC. Gunasekaran et al. (2017) further argued that BDAC could be created by combining quality information sharing and data connectivity, which are an integral part of TR. To be efficiently used and converted to BDAC, big data require new database technologies and robust infrastructure for handling big data in colossal magnitudes (Dubey et al., 2019a). As per Mikalef et al. (2017), big data initiatives in organisations need considerable investments and an adequate period to translate into measurable business value owing to the novel nature of big data and allied tasks and technologies. Moreover, many organisations are unaware of standard operating procedures (SOPs) to execute big data initiatives successfully. Therefore, based on previous studies, it can be hypothesised that

H1: TR has a positive influence on BDAC applied in TSCs

3.2 Human Skills and Big Data Analytics Capabilities

Tourism is often the breadwinner sector promoting human and tangible capital collection, innovation, and technology. New management styles and skills are imperative to sustain the rising demand of data-focused societies (Dubey et al., 2019a). In their study, Gupta & George (2016) also argue that Human Skills (HS) are crucial for developing big data capability. HS comprises leadership qualities, experience, relationships with others, business acumen, knowledge, and problem-solving abilities (Akhtar et al., 2018).

Past research on information technology capabilities suggests that managerial and technical skills (TS) are vital factors in HS with regard to IT (McAfee et al., 2012). Technical 'big data' skills can be explained as the presence of TS and the expertise needed to operate the latest technology to gain knowledge from data (Dubey et al., 2019a). These skills further comprise machine learning and programming competencies, data extraction and cleaning, and relevant statistical analysis techniques (Lozada et al., 2019).

According to Gupta and George (2016), the development of managerial skills (MS) is specific to the organisation and diversely dispersed across it. Cordial working relationships and mutual trust among big data executives and different organisational managers promote exceptional human big data abilities that can be challenging for other firms to replicate (Akhtar et al., 2018). These skills will also include planning, organising, controlling, and implementing big data-related resources, along with the effective application of intelligence extracted from the data to various parts of the organisation. Thus, we propose the following hypothesis:

H2: HS has a positive influence on BDAC applied in TSCs

3.3 Intangible Resources and Big Data Analytics Capabilities

Intangible resources (ITR) are considered the most critical for the industry's supply chain performance among the three main types of organisational resources identified in the RBV (Gupta & George, 2016). Most intangible resources meet the value, rarity, imperfect imitability, and non-substitutability (VRIN) status of an organisation’s resource-based view. This makes them significantly heterogeneous across firms (Teece, 2014). Data-driven and organisational cultures are ITR which can be the basis of extensive heterogeneity among firms looking to acquire value from big data (Gupta & George, 2016). As stated by Mikalef et al. (2018), to effectively deploy big data initiatives across an organisation, big data-driven culture (BDC) and Organisational learning (OL) are required.

In this context, organisational culture improves a company's capability to benefit from big data (Shamim et al., 2019). Data-driven culture can be defined as the degree to which managers at any position in the firm make decisions supported by insights derived from the data (Lozada et al., 2019). Hence, an organisation's capability to accumulate, explore, transform, and share knowledge comprises a critical inventory of valuable knowledge which can be used to form BDAC (Gupta & George, 2016). A high degree of OL facilitates a knowledgeable decision-making process in the firm by validating and combining information with intelligence extracted from big data (Lozada et al., 2019). Hence, based on existing literature, it can be hypothesised that

H3: ITR has a positive influence on BDAC applied in TSCs

3.4 Big Data Analytics Capabilities and Social Performance of Tourism Supply Chains

Based on Gunasekaran and Spalanzani's (2012) contribution, it can be argued that business ethics and social values are important in the success of a sustainable SC in an organisation. That BDAC is found to have a noteworthy influence on social performance (SP), as it helps in successfully establishing equality among gender, better health facilities, safe drinking water, environmental protection, and addresses many more relevant social issues (Dubey et al., 2019b). BDAC is considered one of the important factors of organisational capability, which has the potential to improve SP without compromising financial conditions (Teece et al., 1997; Keeso, 2014). According to Song et al. (2018), social challenges have created a more sustainable supply chain. Established in the existing literature, it is hypothesised that

H4: BDAC has a positive influence on the Social Performance of TSCs

3.5 Big Data Analytics Capabilities and Environmental Performance of Tourism Supply Chains

Big data assists in arranging unstructured information and reducing the chances of loss of information (Li et al., 2018). BDAC improves environmental decision-making by providing timely and accurate information. It provides relevant information to customers and helps them select environmentally friendly products (Xia et al., 2022). BDAC was argued to be a crucial source for improving the channel of distribution and helped in the rapid recovery of supply chain disruptions (Dubey et al., 2019a). Theodoulidis et al. (2017) contended that a company's overall performance is affected by environmental performance (EP). The extant literature has widely accepted the influence of EP on a company's total profits (Rao and Holt, 2005). However, Wamba et al. (2020) argued that BDAC helps organisations achieve their desired performance by optimising environmental dynamics. Based on the existing literature, can be hypothesised as follows:

H5: BDAC has a positive influence on the Environmental Performance of TSCs

3.6 Big Data Analytics Capabilities and Economic Condition of Tourism Supply Chains

Economic conditions (ECOP) in tourist-generating countries influence the demand for tourism products at a particular destination (Zhang et al., 2018). Researchers have argued that tourism contributes to foreign exchange reserves and creates jobs, which leads to the country's economic development (Ohlan, 2017). To achieve a sustainable environment, Zhu & Sarkis (2004) defined economic performance as "financial returns that can result from the adoption of green supply chain initiative". Further, Xia and Tang (2011) argued that BDAC helps compress the supply chain, reduces the cost involved in managing suppliers, develops an active supply channel, and reduces inventory wastage.

BDAC acts as an enabler in manufacturing and operations management for monitoring business processes (Zhan & Tan, 2020), increasing the supply chain's visibility, improving production and manufacturing mechanisation, and enhancing business change (Wamba et al., 2017). The big data dimensions have been characterised as 'Volume', which refers to the amount of data produced; 'Velocity' here means the speed at which data is produced, examined, and acted upon; 'Variety' means structural heterogeneity in a dataset; 'Veracity' means assuring the quality of data, verifying unreliable data and 'Value' signifies big data's economic advantages (Kumar & Chakraborty, 2022). Based on the existing literature, the following hypothesis is proposed.

H6: BDAC has a positive influence on the Economic Performance of TSCs

3.7 Dynamic Capabilities and Tourism Supply Chain Performance

The success of BDAC in creating effective and sustaining TSC performance depends on the dynamic capabilities of TSCs. Sher and Lee (2004) defined dynamic capabilities as an organisation's method of responding to an increasingly fluctuating environment. According to Wamba and Akter (2019), robust dynamic capabilities offer the firm a prime benefit through effective strategies, reduced reaction times, and increased customisation. DC influences a firm's operational capabilities and promotes competitive advantage, thereby positively impacting performance (Wilden et al., 2013).

According to Akter et al. (2020), DC in the tourism industry comprises effective coordination with all stakeholders, collaboration in demand prediction between the firm and business partners, and redesigning business processes to create new productive assets. In support of this, Mandal (2018) states that DC helps TSC firms adjust to fluctuations in the environment and enhance TSC performance. Although DC have received adequate attention in the big data literature (Sun et al., 2018), little research has been conducted to explore the influence of DC on BDAC and performance relationships.

As per Wang et al. (2016), DC helps form sustainable supply chain performance by focusing on improved coordination among various tourism sectors. DC depends on the company's capability to leverage and implement additional potential resources (Mikalef et al., 2019). Therefore, it is suggested that DC may improve the direct impact of BDAC on the TSC performance. Based on this argument, it can be suggested that DC may improve the impact of BDAC on a company's supply chain performance in the tourism sector. Hence, we propose the following hypothesis:

H7a: DC moderates the relationship between BDAC and the Social Performance of TSCs.

H7b: DC moderates the relationship between BDAC and the Environmental Performance of TSCs.

H7c: DC moderates the relationship between BDAC and the Economic Performance of TSCs.

Hence, a proposed framework is conceptualized, as presented in Figure 1.

[Insert Figure 1 about here]

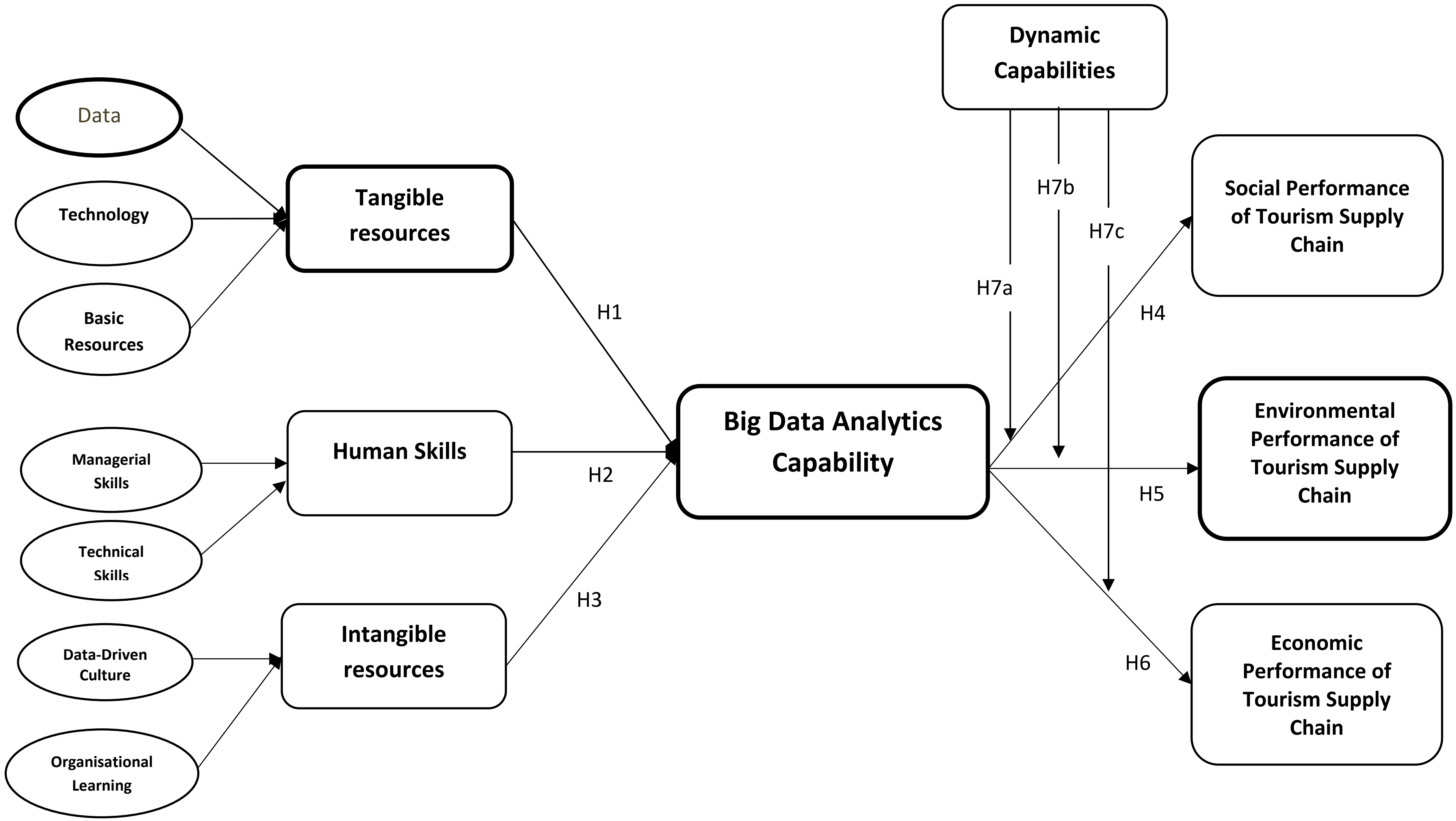

Figure 1: Proposed theoretical framework (*Source: Authors own work)

4. Research Methodology

4.1 Scale Development

Items for the present investigation were selected from allied literature and modified to suit and fit BDAC in context of the tourism sector. In agreement with the methods recommended by Churchill (1979), the scales were modified to match the study context and ensure that they were valid for the tourism industry actors (Appendix A).

A professional group of nine experts working in the tourism sector and three practitioners were consulted for item development related to the tourism industry. The content validity of the study was assessed by an experienced group of nine analytics academicians. A pilot survey was conducted with 56 respondents participating in diverse tourism IT groups on the aforementioned platform. This ensured that the proposed framework was checked for robustness before data collection. A 5-point Likert scale was used to measure all items. The present study controlled for two variables of demographics critical to tourism analytics, the size of the company and experience, to prevent any bias due to demographics. As gauged by employee number, company size was controlled for in the study, as larger firms may possess extra assets and resources for executing supply chain initiatives more effectively in an ever-changing business environment. This may lead them to attain better performance than smaller firms (Mikalef et al., 2019; Tortorella et al., 2020). Company experience, measured by the number of years of experience in the present big data-enabled tourism firm, was also controlled to prevent bias due to demographics (Rialti et al., 2019). The framework of the methodology is shown in Figure 2.

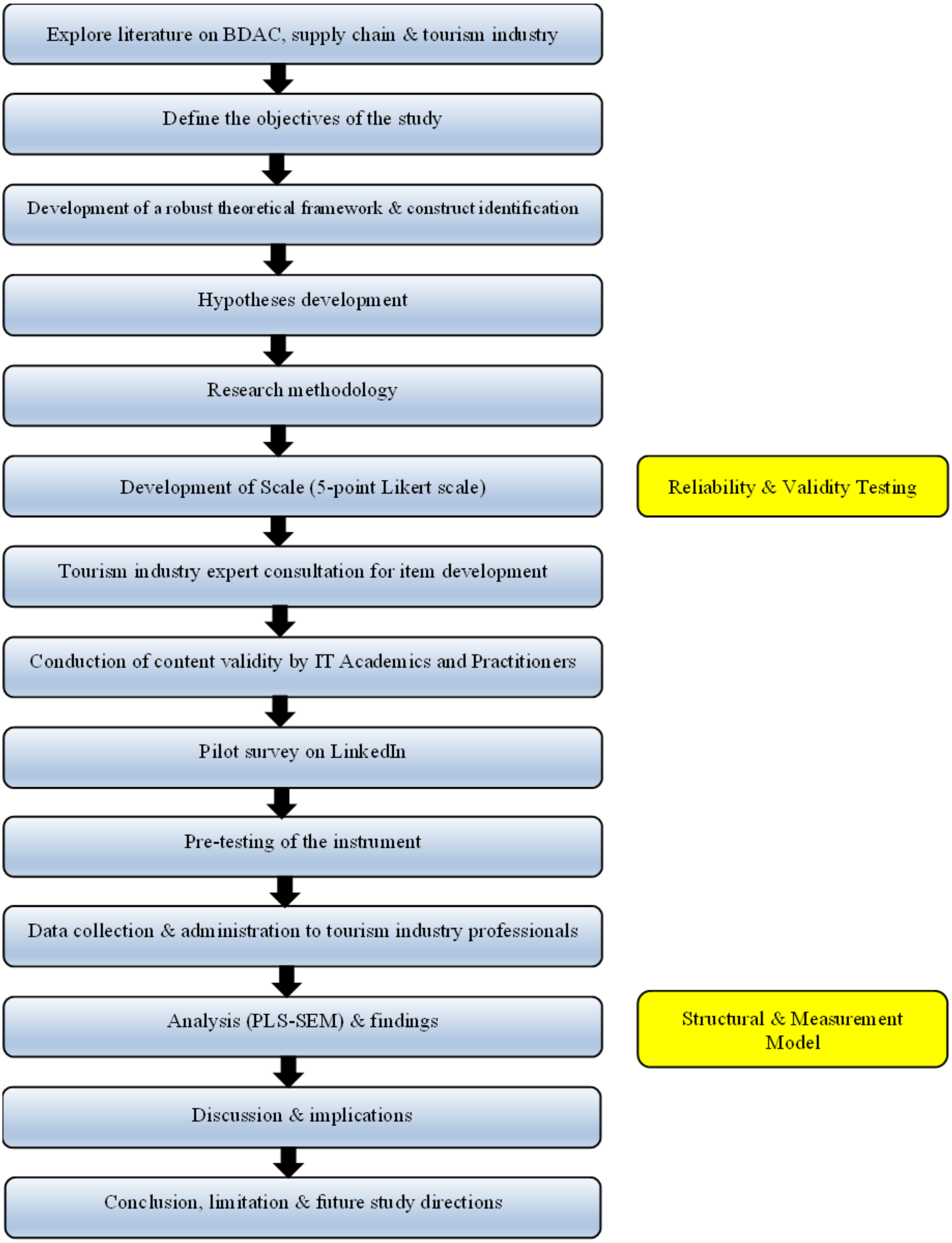

Figure 2: The methodology framework followed in the study (*Source: Authors own work)

4.2 Data Collection

The study items were adapted from well-established sources to confirm the reliability and validity of the measures. The reliability of the scale was also investigated using internal consistency analysis (Table 3). Cronbach's alpha values for data connectivity (0.868), technology (0.894), basic resources (0.843), managerial skills (0.902), technical skills (0.893), big data culture (0.894), organisational learning (0.869), dynamic capability (0.946), environmental performance (0.856), economic performance (0.873), and social performance (0.904) all indicated high internal consistency. Values were above the threshold of 0.70, signifying the reliability of the constructs (Hair et al., 2010). This research aimed to collect responses from various sectors of the tourism industry to gain clarity of perspective and acquire a correct representation of the tourism industry's current condition (Lee & Fernando, 2015).

The Indian Association of Tour Operators (IATO) webpage was accessed to search for links between tourism establishments operating in a particular sector to collect the contacts for this paper. By following snowball sampling (Eze et al., 2023; Rahi, 2017) the research team used their accounts to invite tourism professionals to participate and asked them to further distribute the questionnaire to their friends in the tourism sector. The research rationale, definitions of the main terms, and response anonymity assurance are contained in the cover letter, which comprises definitions of BDAC, DC, and TSC performance. Moreover, the participants were requested to offer a response-building on their learning and experience as the main part of the tourism sector. Sufficient face validity of the responses was ensured through these steps. After putting rigour efforts by the research team members, 218 responses data were collected and used for analysis. Table 2 presents the sample characteristics.

Table 2: Sample characteristics

Demographic Variable	Frequency	Percentage
Gender		
Male	154	70.64
Female	64	29.36
Size of the company		
Less than 50	81	37.15
50–100	49	22.48
101–500	56	25.69

501-1000	32	14.68
Total-experience		
0–3	73	33.48
3–5	32	14.68
5–10	16	7.34
10–15	55	25.23
Above 15 years	42	19.27
Education level		
Graduate	72	33.03
Postgraduate	121	55.50
PhD	25	11.47
Tourism industry units		
Hotels	45	20.64
Travel Agencies	31	14.22
Restaurants	47	21.56
Airlines	23	10.55
E-travel portals	28	12.84
Transportation	26	11.93
Entertainment	18	8.26
Current position/designation		
CEO/COO/CIO	7	3.21
Managing Director/Executive Director	9	4.13
Vice President/ Assistant Vice President	8	3.67
Tourism Manager	27	12.39
Travel Consultant	21	9.63
Analyst	35	16.06
Engineer	28	12.84
Supervisor/Coordinator	23	10.55
Airline Staff	10	4.58
Tour operators	31	14.22
Tour guide	19	8.72

*Source: Authors own work

It is observed that not only top-level management personnel but also analysts and engineers are involved in decisions related to technology implementation in tourism firms. The involvement of these people/personnel is comparatively higher, as they manage the huge amount of data collected on a day-to-day basis. Further, the authors have collected data from those involved in implementing the data-related technology in the organisation. This data collection procedure from various entities is well-recognised (Mandal & Dubey, 2020).

5. Analysis and Findings

A repeated indicator approach was applied to calculate all dimensions simultaneously rather than separate calculations of higher-order and lower-order constructs (Zhang et al., 2018). This study postulates that the measurement mode is reflective (Chin, 2010). Specifically, variations in construct cause variation in the measures, as the measures employed in the present study are manifestations of constructs. A first-order assessment of the reflective measurement model results is presented in Table 3.

Table 3: First order assessment of measurement model

Constructs	α	Items	Loading	CR	AVE
Data Connectivity (DATA)	0.868	DATA1	0.871	0.919	0.791
		DATA2	0.908		
		DATA3	0.889		
Technology (TCH)	0.894	TCH1	0.861	0.922	0.703
		TCH2	0.844		
		TCH3	0.848		
		TCH4	0.844		
		TCH5	0.792		
Basic Resources (BR)	0.843	BR1	0.935	0.927	0.864
		BR2	0.924		
Managerial Skills (MS)	0.902	MS1	0.85	0.931	0.772
		MS2	0.891		
		MS3	0.888		
		MS4	0.886		
Technical Skills (TS)	0.893	TS1	0.878	0.926	0.757
		TS2	0.842		
		TS3	0.863		
		TS4	0.897		
Big Data Culture (BDC)	0.894	BDC1	0.914	0.934	0.825
		BDC2	0.907		
		BDC3	0.905		
Organisational Learning (OL)	0.869	OL1	0.862	0.91	0.717
		OL2	0.855		
		OL3	0.838		
		OL4	0.833		
Dynamic Capability (DC)	0.946	DC1	0.805	0.956	0.757
		DC2	0.876		
		DC3	0.899		
		DC4	0.898		
		DC5	0.875		
		DC6	0.884		
		DC7	0.85		
		EP1	0.822		

Environmental Performance (EP)	0.856	EP2	0.847	0.903	0.699
		EP3	0.835		
		EP4	0.84		
Economic Performance (ECOP)	0.873	ECOP1	0.853	0.913	0.723
		ECOP2	0.853		
		ECOP3	0.849		
		ECOP4	0.846		
Social Performance (SP)	0.904	SP1	0.887	0.933	0.776
		SP2	0.917		
		SP3	0.845		
		SP4	0.874		
		Items	**Weights**	**t-value**	**VIF**
Control Variables		Size	0.634	1.372	1.673
		Experience	0.367	1.742	1.535

α = Cronbach's alpha

*Source: Authors own work

The present model was assessed and evaluated using partial least squares (PLS) path modelling, This technique requires less model complexity and higher theoretical parsimony (Tasci & Godovykh, 2021). Undoubtedly, partial least squares is considered more appropriate for hierarchical model estimation than structural equation modelling (SEM), as PLS can effectively deter the constraints on measurement level, model complexity, distributional properties, sample size, factor indeterminacy, and model identification (Hair et al., 2011). Aimed at internal approximation, SmartPLS 3.3.2 was employed for model estimation with a path-weighting scheme (Ringle et al., 2014). Non-parametric bootstrapping (Tenenhaus et al., 2005) was applied in the study with 5000 repetitions to achieve standard errors of estimates (Hair et al., 2013). Values of second-order and first-order constructs were calculated repetitively using the same indicator number (Chin, 2010). A third-order BDAC dimension was formed that characterizes all indicators of the first-order variables.

5.1 Measurement Model and Higher-Order Measurement Model

The convergent and discriminant validity of the measurement model (first-order) was confirmed using confirmatory factor analysis (CFA) (see Table 3). Data (DATA), technology (TCH), BR, MS, TS, BDC, and OL are the constructs that combine to form first-order constructs. Item loadings that were more than the threshold values (0.7 were calculated (Hair et al., 2013), and values were also significant ($p < 0.001$). A finer range of differences between the item loadings and a higher average demonstrates that the respective items measure the underlying construct more robustly (Chin, 2010). The composite reliability (CR) and average variance extracted (AVE) were evaluated (Fornell and Larcker, 1981). AVE and CR specify the degree of association between the indicators and their underlying constructs to check the reliability of the measurement scale. The AVE of all scales was equal to or exceeded the threshold value of 0.05. Similarly, all scales have a CR value equal to or higher than the cutoff value of 0.80 (Hair et al., 2013). Accordingly, 0.699 is the lowest AVE for EP and 0.903 is the lowest CR for EP.

The square root of the AVE was calculated in the diagonals of the correlation matrix (Table 4). All values surpass the suggested cut-offs. Hence, satisfactory convergent validity and reliability were confirmed as the item loadings and estimates of AVE and CR surpassed their respective thresholds (Fornell and Larcker, 1981). Moreover, the research observed for the formative control variables, the factor weights of the size of the company and experience were significant ($p < 0.01$). The company size and experience Variance Inflation Factor (VIF) is found to be 1.673 and 1.535, which is less than the threshold value of 3. This proves that the collinearity test is acceptable for the model.

Table 4: Descriptive statistics, AVEs, and correlations

Construct	Mean	S. D.	BR	BDC	DATA	DC	EP	ECOP	MS	OL	SP	TS	TCH
BR	3.796	0.994	0.930										
BDC	3.682	1.127	0.614	0.908									
DATA	3.789	0.990	0.595	0.643	0.889								
DC	3.602	1.086	0.534	0.655	0.617	0.870							
EP	3.483	1.012	0.348	0.393	0.468	0.435	0.836						
ECOP	3.725	1.038	0.507	0.526	0.521	0.734	0.439	0.851					
MS	3.855	1.016	0.577	0.641	0.656	0.558	0.344	0.507	0.879				
OL	3.836	1.000	0.478	0.513	0.574	0.486	0.361	0.650	0.556	0.847			
SP	3.681	1.036	0.486	0.558	0.567	0.624	0.581	0.483	0.463	0.406	0.881		
TS	3.726	1.050	0.588	0.618	0.642	0.594	0.373	0.502	0.559	0.480	0.554	0.870	
TCH	3.667	1.021	0.480	0.570	0.603	0.568	0.408	0.440	0.498	0.497	0.510	0.551	0.838

*Source: Authors own work

Discriminant validity is established as the aforementioned values; in the first-order model, it surpasses constructs' inter-correlations with other constructs (Fornell and Larcker, 1981). This signifies that the constructs are conceptually different. Furthermore, they do not comprise or share similar items (Chin, 2010). To further justify discriminant validity, cross-loadings were examined, which showed that an item loaded extra on its underlying dimension rather than on a different dimension. This also means that the items are intensely similar in their particular dimensions. Furthermore, a significant amount of variance is shared among all dimensions with their items (Fornell and Bookstein, 1982). In all cases, a shared variance of 55% (that is, 0.74*0.74) and above was observed in the item's relationship with their constructs. This value is considerably large in magnitude compared with different dimensions. Overall, the measurement model was deemed suitable owing to the presence of satisfactory convergent validity (loadings > 0.75), reliability (CR > 0.90, AVE > 0.50) (see Table 3), and discriminant validity (√AVE > correlations), as shown in Table 4. The measurement model was hence proven suitable, and it was further engaged in examining the third-order model (Chin, 2010). Table 5 shows the calculations of the third-(BDAC) and second-order reflective measurement models (TR, HS, and ITR).

Table 5: Calculation of third and second-order reflective measurement model

Models	Constructs	AVE	CA	CR	Dimensions	β	R^2	*t*-stat
Third-order	BDAC				TR	0.423		19.597
		0.480	0.954	0.958	ITR	0.308		16.515
					HS	0.361		19.833
Second-order	Tangible skills				BR	0.240	0.713	16.336
		0.550	0.909	0.924	DATA	0.380	0.935	21.572
					TCH	0.554	0.980	30.053
	Intangible skills				BDC	0.539	0.923	21.722
		0.578	0.878	0.906	OL	0.610	1.024	28.015
	Human skills	0.596	0.903	0.922	MS	0.574	0.961	30.216
					TS	0.559	0.956	24.221

*Source: Authors own work

Both second- and third-order constructs are higher-order. The third-order BDAC dimension comprises 25 items (10+8+7), of which ten items (3+5+2) represent TR, eight items (4+4) represent HS, and seven items (3+4) represent ITR. In this study, reflective is the characteristic of higher-order constructs; item loadings of both second-order constructs (TR, HS, ITR) and third-order constructs (BDAC) were found to be significant at $p < 0.05$. Their first-order antecedents describe the degree of variance of the second-order constructs (see Appendix A). That is, the degree of explained variance in TR was described by BR (71.3%), DATA (93.5%), and TCH (98%). ITR was described as BDC (92.3%) and OL (92.4%). Finally, HS was described as MS (96.1%) and TS (95.6%). The path coefficients (β) distributed from the first-order to the third-order construct were significant at $p < 0.01$. TR had a positive influence on BDAC (*Î²* = 0.423, $p < 0.001$). Thus, it can be argued that H1 is supported. Similarly, the HS ($\beta = 0.361$, p < 0.001) and ITR ($\beta = 0.308$, $p < 0.001$) were positively associated with BDAC. Therefore, H2 and H3 were supported.

5.2 Structural Model

To validate the structural model, the association between higher-order BDAC and the performance of TSCs, that is, ECOP/EP/SP, was examined. The standardised beta for the paths BDAC-SP, BDAC-ECOP is 0.260, and BDAC-EP was 0.393, 0.260, and 0.363, respectively, thus supporting H4, H5, and H6. The moderating effect of DCs on ECOP/EP/SP was calculated by applying an interaction effect on SmartPLS 3.3.2 (Akter et al., 2011).

Hence, to assess the interaction effect (Akter et al., 2016), the researchers individually calculated the impact of BDAC on SP, BDAC on ECOP, BDAC on EP, DC on SP, DC on ECOP, DC on EP, and the influence of BDAC*DC on SP, ECOP, and EP. For the interaction model, the calculated standardised β for BDAC–SP ($p < 0.01$) was 0.38, BDAC–ECOP ($p < 0.01$) was 0.373, BDAC–EP ($p < 0.01$) was 0.396, DC-SP ($p < 0.01$) was 0.34, DC-ECOP ($p < 0.01$) was 0.17, DC-EP ($p < 0.01$) was 0.536, and for BDAC*DC-SP ($p < 0.05$) was − -0.02, BDAC*DC-ECOP ($p < 0.05$) was 0.168, and BDAC*DC-EP ($p < 0.05$) was 0.049.

The results verify the significant impact of moderator DC on the path coefficient of BDAC*DC-ECOP and the relationship between BDAC and ECOP, and DC-ECOP in the interaction model (Dubey et al., 2019a). Table 6 presents the main and interaction models, showing that R^2 is significantly improved by incorporating the moderating variable (DC) for SP/EP/ECOP. The size of the moderating effect (f^2) is 0.139, which represents a medium effect (Akter et al., 2016), however, it is significant at $p < 0.05$. Hence, the findings support H7c. In addition, the moderating effects of BDAC*DC-SP and BDAC*DC-EP are insignificant, as the values of f^2 are 0.001 and 0.007, respectively.

Table 6: Structural Model

Main Model	**Path Coeff.**	**Standard error**	***t*-statistic**	R^2	f^2
BDAC -> ECOP	0.260		2.744	0.570	
BDAC -> EP	0.363		3.611	0.252	
BDAC -> SP	0.393		3.927	0.463	
Interaction Model					
BDAC -> ECOP	0.373	0.006	4.303	1.09	0.139
BDAC -> EP	0.396	0.006	4.013		0.067
BDAC -> SP	0.380	0.006	4.001		0.099
DC -> ECOP	0.171	0.006	6.153		0.523
DC-> EP	0.536	0.006	1.777		0.017
DC -> SP	0.340	0.006	3.547		0.113
BDAC*DC -> ECOP	0.168	0.004	3.426	0.715	0.139
BDAC*DC -> EP	0.049	0.003	0.85	0.308	0.007
BDAC*DC -> SP	-0.021	0.004	0.376	0.523	0.001
Control Model					
BDAC -> ECOP	0.277		3.543	0.575	
BDAC -> EP	0.360		2.654	0.253	
BDAC -> SP	0.373		1.633	0.468	

Size -> ECOP	-0.020
Size -> EP	0.044
Size -> SP	-0.032
Exp -> ECOP	-0.055
Exp -> EP	0.026
Exp -> SP	0.060

*Source: Authors own work

Thus, the results verify the better prediction capability of the interaction model, which is exhibited in the ECOP of the firm (R^2 = 0.715, f^2 = 0.139, p < 0.01). Likewise, the researchers examined the effect of control variables, that is, the size of firm and experience of an employee on SP/EP/ECOP, which was found to be insignificant as the change in R^2 observed was very small. Figure 3 shows the structural model used in this study.

[Insert Figure 3 about here]

5.3 Additional Analysis

Furthermore, the nomological validity of the overall model was analysed after validating the impact of BDAC and DC on ECOP/EP/SP. Additional analyses were conducted to confirm the overall authenticity of the study. The non-response bias, calculated with the help of the Student's t-test on all the variables of responses, was computed in two groups: first, the respondents who replied early within the first two weeks and a second group who reverted in the last two weeks (Mikalef et al., 2019). The results for the items studied in both groups did not reveal any significant differences. Second, Harman's one-factor test was conducted to evaluate the severity of Common Method Bias (CMB) on first-order constructs (Dubey et al., 2019a; Hair et al., 2013). The value of single factor maximum covariance calculated was 44 %, which is less than 50%, indicating that there was no significant common factor loading on all items. Further, predictive validity was calculated using Stone-Geisser's Q^2 (Hair et al., 2016). Applying a cross-validated redundancy approach with an omission distance of seven in SEM-PLS (Akter et al., 2011), the value of Q^2 was 0.414 for ECOP, 0.172 for EP, and 0.352 for SP, which positively exemplifies the predictive validity of BDAC on ECOP (Chin, 2010). Table 7 presents the hypothesis results derived as per the β and p-values.

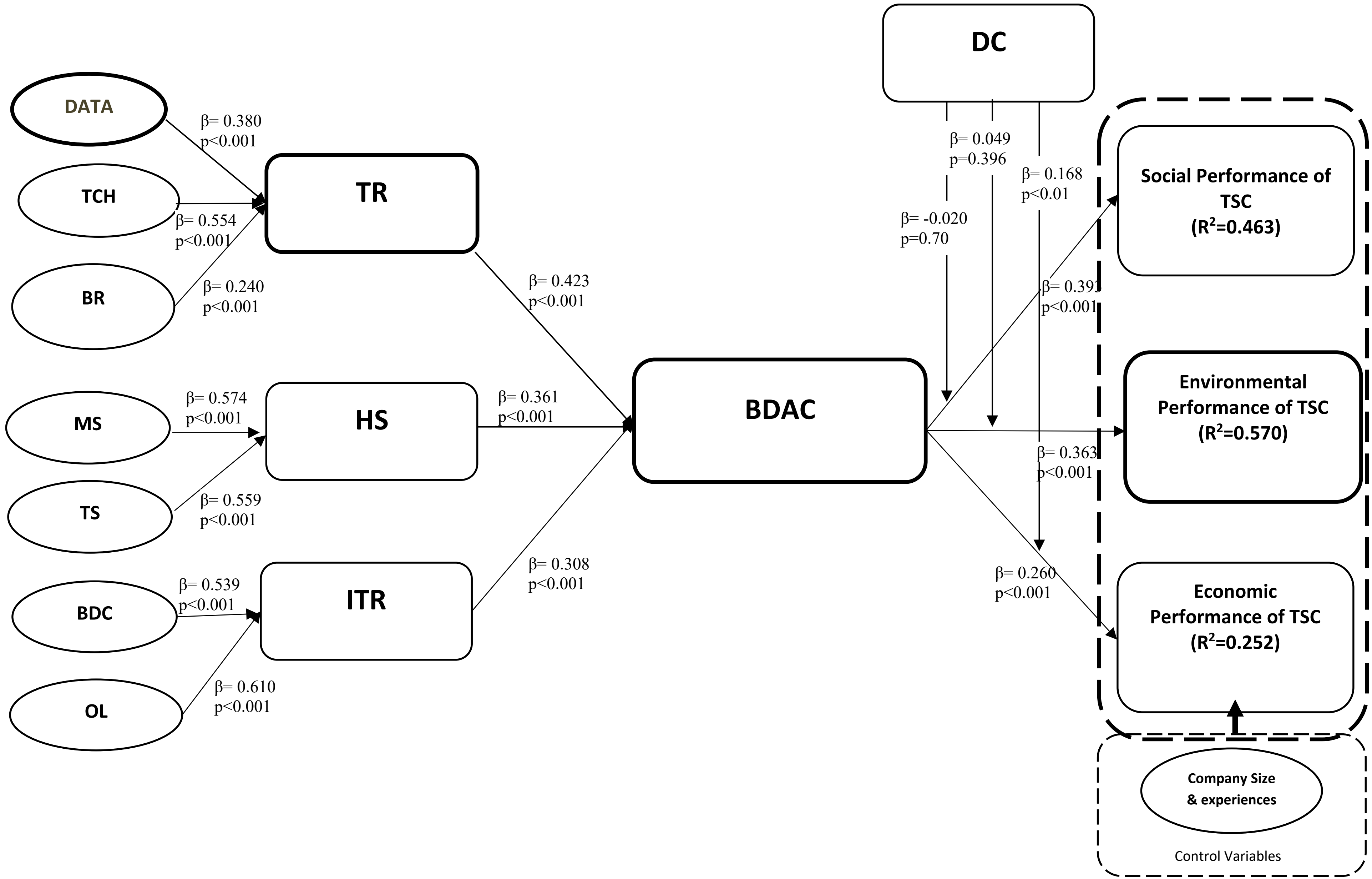

Figure 3: Structural Model (*Source: Authors own work)

Table 7: PLS hypothesis results derived as per β and p-values

Hypothesis	Effect of	On	*B*	*p*	Result
H1	TR	BDAC	0.423	$p < 0.001$	Supported
H2	HS	BDAC	0.361	$p < 0.001$	Supported
H3	ITR	BDAC	0.308	$p < 0.001$	Supported
H4	BDAC	SP of TSCs	$\beta = 0.393$	$p < 0.001$	Supported
H5	BDAC	EP of TSCs	$\beta = 0.363$	$p < 0.001$	Supported
H6	BDAC	ECOP of TSCs	$\beta = 0.260$	$p < 0.001$	Supported
H7a	DC+BDAC	SP of TSCs	$\beta = -0.02$	$p = 0.70$	Not supported
H7b	DC+BDAC	EP of TSCs	$\beta = 0.049$	$p = 0.30$	Not supported
H7c	DC+ BDAC	ECOP of TSCs	$\beta = 0.168$	$p < 0.01$	Supported

*Source: Authors own work

6. Discussion and Implications

In the tourism industry, the value of BDA has been challenged by various researchers since it has been claimed that only a small proportion of tourism-based companies have had the opportunity to secure the entire perspective of their investments made in big data (Ross et al., 2013). Big companies are continually discussing big data analytics power in business, but not much empirical testing has been done in the area of tourism (Gupta & George, 2016).

This study hypothesises the positive influences of various resources on BDAC in the tourism sector, namely TR, ITR, and HS. The results support past findings, such as those of Kalyar et al. (2019), who asserted that TR, ITR, and HS enhance BDAC. Additional conclusions are supported by Dubey et al. (2019a) and (Mikalef et al., 2019), who show that TR, ITR, and HS have positive and significant path coefficients.

Second, with the increasing prominence of the data, our research has significant implications for the tourism industry. Our research shows that BDAC is an important facilitator of SP, EP, and ECOP, thus affirming the link between BDAC and firm performance indicators (SP, EP, and ECOP), supporting Wamba et al. (2017). Furthermore, our research findings also highlight the harmonisation between BDAC and DC to attain improved economic performance (ECOP). These findings are consistent with those of Kim et al. (2011), who found an alignment between BDAC and firm performance by focusing on DC. Thus, this study hypothesises a positive moderation of DC on the influences of BDAC on economic performance, environmental performance, and social performance in the tourism sector. Environmental performance is a worrying issue in the business world. However, the moderating role of DC between BDAC and environmental performance was not observed on statistical grounds, which supports Jermsittiparsert et al. (2019), who state that green logistics plays a key role in upgrading the environmental performance of the supply chain. These results were not consistent with previous findings in other sectors, such as the Agri Food Sector (Trivellas et al., 2020). However, the impact of BDAC on economic performance is significant because of the costs involved and ad hoc problem-solving techniques. Large and successful hotels, airlines, and restaurants can easily implement these systems.

On the other hand, DC in social management may require more time to develop, implement, and bring performance benefits compared to static advantages (Hong et al., 2018). Therefore, with the help of dynamic capability, BDAC had no significant impact on social performance in the present study. Similarly, embedding BDAC and dynamic capability with respect to environmental functions requires companies' collaboration with important stakeholders to significantly improve EP (WEF, 2020). Thus, the BDAC dynamic capability does not have a significant impact on environmental performance, as in the present study. Not many tourism firms integrate sustainability into their operations, as the sector is growth-oriented, with the main focus being generating an attractive return on investment to satisfy the important stakeholders involved (WEF, 2017; The Hindu, 2022). Furthermore, few studies have provided insights into how DC can affect SP and EP (Carter & Easton, 2011; Hong et al., 2018). Complementing such studies, this study shows that the direct rationale for BDAC acceptance is predicated on economic rationality rather than on environmental or social motives.

6.1 Theoretical Implications

This study provides many unique theoretical implications for interpreting the association between the resources of a company, BDAC, and DC, and the performance of the company, that is, ECOP/EP/SP. The theoretical structure in Figure 1 represents pragmatic assistance towards the resilience of upgrading skills while DC exists in the firm (Scholten & Schilder, 2015), thereby extending the literature on big data analytics and showcasing improved knowledge related to the impact of big data dynamism and strategies for improving the performance of a firm.

The results of this study indicated that BDAC had a significant impact on ECOP/EP/SP. Therefore, it can be said that the results suggest that BDAC can accelerate the ECOP/EP/SP of a tourist firm. Earlier studies by Keeso (2014) and Song et al. (2017) asserted that BDAC directly affects SP and EP in the presence of DC. Thus, it can be claimed that the research findings continue to expand the research of previous researchers who concluded that BDAC has adequate possibility to enhance ECOP/EP/SP in the tourism industry using DC as a moderator. This study found that DC has a remarkable impact only on ECOP. Second, the present research emanates from the RBV and dynamic capabilities, with the support of which a multidimensional BDAC model is conceptualised. The results validate BDAC as a hierarchical construct that strongly influences firm performance, that is, ECOP/EP/SP.

This study demonstrates the importance of BDAC as a source of company performance. Third, the study attempts to exhibit the complicated phenomenon of implementing BDA in a firm using RBV within a big data environment. The multidimensional constructs developed in the research model prove that the model not only accepts structural parsimony but also explains the theoretical relations between the items at the first-order, second-order, and third-order constructs. Finally, this research also evaluates and computes the moderating effect of DC on a firm's performance, which may be added to the literature on BDA. The findings on the moderating effect of DC explain the theoretical model more explicitly and widen its contribution by explaining the effect of the BDAC model on firm performance, which supports Iacobucci's (2009) study. Overall, the study results also help reduce intricacies regarding dynamic capabilities in RBV theory (Teece, 2014).

6.2 Managerial Implications

In the context of BDA, TR, ITR, and HS are essential components of BDAC and act as influential predictors of ECOP/EP/SP. As a model, the performance of TR can be enhanced by improving the data connectivity, technology used, and high-quality basic resources. Similarly, ITR can be improved by enhancing the big data culture and organisational learning. Second, the empirical results indicate that DC offers to improve the ECOP of firm initiatives undertaken in implementing BDA, while tourism industry practitioners still need to give more consideration to environmental and social factors. Explicitly, it is believed that the firm will have a similar success despite the business's size change.

Finally, HS can be upgraded by improving the technical and managerial skills of the workforce. Thus, the results suggest that the overall enhancement of BDAC is associated with the dimensional and sub-dimensional levels. This research will assist managers facing a dilemma about when and how BDAC can be used to enhance the performance of tourism-related businesses. Since, big data technology and tools are designed to handle and analyse large volumes of data, which makes it possible to be implemented in all sizes of organisations to gain valuable insights from their data. However, the scale of data and the level of analytical capability required will vary depending on the size and complexity of the organisation. Smaller tourism-related enterprises can use big data analytics to gain insights into customer behaviour and preferences, which can then be used to personalise their services and marketing efforts. Larger tourism enterprises can use big data analytics to analyse market trends and consumer behaviour, making informed decisions on product and service offerings. Thus, it can help in improving customer experiences, increase efficiency, and drive business growth. The TSCs can use big data analytical capabilities in identifying and integrating relevant data sources, such as customer data, operational data, and market data, to ensure that the data being analysed is comprehensive and relevant. It helps in analysing data on room availability, booking patterns, and pricing, and the business can optimise inventory management, ensuring that rooms are priced correctly and occupied during periods of high demand.

7. Conclusion

This study illustrates the function of the RBV and DCV in proposing a holistic BDAC framework and its impact on TSC performance. Since interest in the tourism sector is continually increasing in business analytics, the present study explores the function of BDAC in improving TSC performance with the help of the moderating role of DC. The availability of fast-moving data with the latest technology to analyse the data and sufficient funds proved to improve the procedures and adopt BDAC to create innovative competencies that focus on value addition in organisations. Hence, TR, ITR, and HS can be considered key resources for attaining a sustainable progressive version of BDAC in a competitive environment.

For example, Zomato is famous for exploring restaurants and making food orders and reservations. Each day, the company works with approximately 40 billion customer messages. This is only possible through the intelligent application of BDA to process a large amount of information (IANS, 2020). Similarly, the Indian Taj Group of Hotels focuses on big data to satisfy informed modern customers' shifting needs and improve relationships with them. The Group purchased the Oracle Sales Automation Cloud to unite and combine many hotel chain features and facets. Thus, the connections in the model provide managers with an understanding of BDAC antecedents and their links to individual capability dimensions (TR, ITR, and HS).

Another significant finding is that changes in the business processes exaggerate the tourism environment, collaboration between the firm's business partners and distributors, and investment in new technologies, which require continuous updating and adaptations (Gupta et al., 2020) to construct DC. Research confirms that a firm’s DC plays a key moderating role between BDAC and ECOP, while it does not exert any moderating influence on the relationships between BDAC and EP, BDAC, and SP.

First, the scope of the study was confined to investigating BDAC factors and demonstrating the effect of BDAC on tourism firm performance with DC as a moderator. Additional dimensions, such as process-oriented DC (Kim et al., 2011) and business agility (Chen et al., 2022), can be integrated into future studies. The second limitation was that certain hot topics could not be included in this research, and the unit of analysis was individuals, not organisations, which could be the limitation of the study and can be considered in future research.

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Appendix A. Survey measures

3rd-order construct	2nd-order constructs	1st-order constructs	Type	Item labels	Items	Sources
Big Data Analytics Capabilities (BDAC)	Tangible resources (TR)	Data connectivity (DATA)	Reflective	**DATA1**	Access to very large and fast-moving data for analysis has a positive impact on the efficiency of the tourism-based firm	*Gupta and George (2016); Gunasekaran et al. (2017)*
			Reflective	**DATA2**	Combing data from multiple sources into a data warehouse has a positive impact on the efficiency of the tourism-based firm	
			Reflective	**DATA3**	Integrating internal and external data assists in business environment analysis which has a positive impact on the efficiency of the tourism-based firm	
		Technology (TCH)	Reflective	**TCH1**	Using parallel computing approaches (e.g. Hadoop) for data processing has a positive impact on the efficiency of the tourism-based firm	
			Reflective	**TCH2**	Using different data visualization tools for analysis has a positive impact on the efficiency of the tourism-based firm	
			Reflective	**TCH3**	Exploring cloud-based services for data processing has a positive impact on the efficiency of the tourism-based firm	
			Reflective	**TCH4**	Adopting new forms of databases such as Not Only SQL(NoSQL) has a positive impact on the efficiency of the tourism-based firm	
			Reflective	**TCH5**	Exploring/ adopting open-source software for big data analytics has a positive impact on the efficiency of the tourism-based firm	

		Basic Resources (BR)	Reflective	**BR1**	Allocation of sufficient funds for big data analytics has a positive impact on the efficiency of the tourism-based firm	
			Reflective	**BR2**	Presence of adequate time to achieve desired results from big data analytics has a positive impact on the efficiency of the tourism-based firm	
	Human skills (HS)	Managerial Skills (MS)	Reflective	**MS1**	The ability of data handling managers to understand the suppliers and customers has a positive impact on the productivity of the tourism-based firm.	*Gupta and George (2016)*
			Reflective	**MS2**	The ability of data handling managers to coordinate big data-related activities between other managers, suppliers and customers has a positive impact on the productivity of the tourism-based firm	
			Reflective	**MS3**	The ability of data handling managers to understand and evaluate the output obtained from big data has a positive impact on the productivity of the tourism-based firm	
			Reflective	**MS4**	The ability of data handling managers to understand where to apply big data has a positive impact on the productivity of the tourism-based firm	
		Technical Skills (TS)	Reflective	**TS1**	The Technical Staff possess the right skills to accomplish their jobs successfully, which has a positive impact on the productivity of the tourism-based firm	

			Reflective	**TS2**	The Technical Staff is well trained, which has a positive impact on the productivity of the tourism-based firm	
			Reflective	**TS3**	Training of big data analytics is provided to the employees, which has a positive impact on the productivity of the tourism-based firm	
			Reflective	**TS4**	The Technical Staff has suitable education to perform their job duties which has a positive impact on the productivity of the tourism-based firm	
	Intangible resources (ITR)	Big data culture (BDC)	Reflective	**BDC1**	Data is treated as a tangible asset, and it has a positive impact on the functioning of the tourism-based firm	*Gupta and George (2016)*
			Reflective	**BDC2**	Decisions are based on data rather than on instinct, and it has a positive impact on the functioning of the tourism-based firm	
			Reflective	**BDC3**	Willingness to override own intuition when data contradict our viewpoints has a positive impact on the functioning of the tourism-based firm	
		Organisational Learning (OL)	Reflective	**OL1**	Ability to acquire new and relevant knowledge has a positive impact on the functioning of the tourism-based firm	
			Reflective	**OL2**	Collective efforts for the exploitation of existing competencies and exploration of new knowledge has a positive impact on the functioning of the tourism-based firm	
			Reflective	**OL3**	Ability to assimilate relevant knowledge has a positive impact on the functioning of	

					the tourism-based firm	
			Reflective	**OL4**	Application of relevant knowledge has a positive impact on the functioning of the tourism-based firm	
	Dynamic Capabilities (DC)		Reflective	**DC1**	Using big data analytics for learning about the macro-market environment positively impacts tourism industry performance	*Akter et al. (2020); Mikalef et al. (2019)*
			Reflective	**DC2**	Constantly renewing the ways of achieving targets and objectives positively impacts tourism industry performance	
			Reflective	**DC3**	Investing in big data analytics for finding solutions for customers positively impacts tourism industry performance	
			Reflective	**DC4**	Providing more effective coordination with customers, business partners, and distributors positively impacts tourism industry performance	
			Reflective	**DC5**	Scanning the environment and identifying new business opportunities positively impacts tourism industry performance	
			Reflective	**DC6**	Collaborating in demand forecasting and planning between firm and business partners positively impacts tourism industry performance	
			Reflective	**DC7**	Reconfiguring our business processes to come up with new productive assets positively impacts tourism industry performance	

	Social performance (SP)	Reflective	**SP1**	Using big data analytics helps in total employment	*Shibin et al. (2017); Dubey et al. (2019b)*
		Reflective	**SP2**	Using big data analytics helps in employee per enterprise	
		Reflective	**SP3**	Using big data analytics helps in average gross wages per employee	
		Reflective	**SP4**	Using big data analytics helps in male vs full-time female employment	
	Environmental performance (EP)	Reflective	**EP1**	Using big data analytics helps in reduction of air pollution	
		Reflective	**EP2**	Using big data analytics helps in reduction of water waste	
		Reflective	**EP3**	Using big data analytics helps in reduction of solid wastes	
		Reflective	**EP4**	Using big data analytics helps in improving an enterprise environmental situation	
	Economic performance (ECOP)	Reflective	**ECOP 1**	Using big data analytics helps organisation to decrease the cost for materials purchasing	*Shibin et al. (2020); Zhu and Sarkis' (2004)*
		Reflective	**ECOP 2**	Using big data analytics helps organisation decrease of cost for energy consumption	
		Reflective	**ECOP 3**	Using big data analytics helps the organisation decrease fee for waste treatment	
		Reflective	**ECOP 4**	Using big data analytics helps the organisation decrease the fee for waste discharge	

*Source: Authors own work