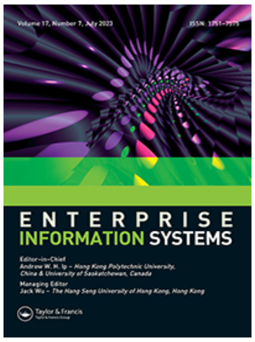

Enterprise Information Systems

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/teis20

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To cite this article: Mahak Sharma, Ruchita Gupta, Rajat Sehrawat, Karuna Jain & Amandeep Dhir (2023): The assessment of factors influencing Big data adoption and firm performance: Evidences from emerging economy, Enterprise Information Systems, DOI: 10.1080/17517575.2023.2218160

To link to this article: https://doi.org/10.1080/17517575.2023.2218160

Published online: 02 Jun 2023.

ENTERPRISE INFORMATION SYSTEMS
https://doi.org/10.1080/17517575.2023.2218160

The assessment of factors influencing Big data adoption and firm performance: Evidences from emerging economy

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ABSTRACT

The current study investigates and prioritizes 17 determinants of big data adoption (BDA) and establishes causality between these determinants' and firms' performance in the tourism and hospitality sector using technology, organisation & environment (TOE) framework. Semi-structured interviews and multi-criteria decision-making (MCDM) were utilized to gather data from 28 industry experts. "Big data quality" ranked as the most influential determinant, while "trading partner pressure" ranked as the least influential determinant. This study's findings highlight the need for governments across the globe to propose and implement policies to reduce the digital divide and enhance standardization.

ARTICLE HISTORY
Received 20 Oct 2021
Accepted 19 May 2023

KEYWORDS
Big data adoption; firm performance; hospitality; Multi-criteria decision-making (MCDM); tourism

1. Introduction

The tourism and hospitality sector has witnessed a massive technological transformation (Fuchs, Höpken, and Lexhagen 2014). It is among the fastest growing sectors in the world, driving exports, creating jobs (over 330 million worldwide) and generating prosperity (nearly 8.8 trillion USD; World Travel and Tourism Council, WTTC 2019). Furthermore, it is projected to become a 492.21 billion USD industry by 2028 (IBEF, 2019). Within this sector, online travel agents (OTAs) are used extensively to explore travel destinations and book flights, hotels and cabs (Talwar et al. 2020b, 2020a). The increased use of OTAs has generated a large amount of data, popularly called big data (Addo-Tenkorang and Helo 2016). This data needs to be utilised in an effective manner so that companies can provide a delightful experience to the user. However, there is no framework that can aid a firm to recognise the impediments or actuators that can assist a firm to execute better in present dynamic setting.

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OTAs generate electronic traces of searches and trip preparation, booking, service consumption and reviews for prospective travellers. Firms must judiciously mine this massive volume of data to increase their business value (Wamba et al. 2015, 2017; Anfer and Wamba 2019; Tandon et al. 2020; Aggarwal and Gour 2020). Scholars suggest that this data mining, known as big data analytics, enables effective evidence-based decision-making and thus facilitates innovations and improves firms' business performance (Wamba et al. 2015; Frisk and Bannister 2017; Acharya et al. 2018; Yadegaridehkordi et al. 2020). Accordingly, big data offers firms both tangible (increased revenue and reduced cost) and intangible benefits (improved consumer satisfaction; Brock and Khan 2017; Grover et al. 2018; Wamba et al. 2020). Similarly, in the context of the tourism and hospitality sector, scholars have emphasised that customers' needs, behaviour and perceptions generate massive amounts of data (Fuchs, Höpken, and Lexhagen 2014; Tan et al. 2021). If it is utilised resourcefully, this big data can offer tourism and hospitality firms valuable insights – for example, regarding the most attractive offers and packages to entice tourists and travellers with excellent service encounters (Fuchs, Höpken, and Lexhagen 2014; Soderlund et al., 2020; Shaikh, Alharthi, and Alamoudi 2020).

Although big data-driven solutions offer novel affordances and benefits to the tourism and hospitality sector, the prior literature on this topic suffers from four major research gaps. First, scholars emphasise that prior work on the applicability of big data in this sector entails various limitations, such as the absence of theoretical grounding, a lack of transparency regarding big data's role and a lack of clarity over its definition and scope (Sena et al. 2019; Line et al. 2020; Rivera 2020; Xu, Nash, and Whitmarsh 2020). They further argue that the extant literature includes only a handful of empirical studies examining the applicability of big data to significant research problems in the tourism and hospitality sector (Wamba et al. 2015; J. Li et al. 2018; Yallop and Seraphin 2020; Shereni and Chambwe 2020). Similarly, Nusair, Butt, and Nikhashemi (2019) highlighted that the applicability of big data-driven solutions in the context of OTAs, particularly in the tourism and hospitality sector, has been insufficiently researched.

Second, our review of the prior hospitality literature on big data suggests that most extant studies are either conceptual or qualitative. In comparison, scholars have undertaken only a limited number of quantitative studies thus far (Sena et al. 2019). For example, multi-criteria decision-making (MCDM) quantitative methods (Sharma and Sehrawat 2020b) are effective for investigating and positioning factors in the domain of adoption of technology (Sharma and Sehrawat 2020a), e.g. the big data adoption (BDA) (Yadegaridehkordi et al. 2018). However, these MCDM methods have not yet been utilised in the literature, specifically in the tourism sector (Yadegaridehkordi et al. 2020).

Third, while the BDA and its influence on firm performance is well-examined in other sectors, such as manufacturing (Yadegaridehkordi et al. 2018) and agri-food (Akhtar et al. 2019), similar studies in the tourism and hospitality sector are almost non-existent (Yadegaridehkordi et al. 2020). Furthermore, a dearth of studies investigates the determinants of BDA among tourism and hospitality firms and elucidates their cause-and-effect (CAE) relationships, which ultimately influence firm performance (Nusair, Butt, and Nikhashemi 2019; Yadegaridehkordi et al. 2020).

Fourth, most prior research works on big data and tourism and hospitality target developed countries, such as New Zealand (Akhtar et al. 2019), the United Kingdom and the United States of America (Sena et al. 2019). However, in

India – the world's second most populous country, the hospitality sector contributes nearly 240 billion USD, equivalent to approximately 9.2% of India's GDP & 9.9% of India's entire employment (42.67 million position of employment; World Travel and Tourism Council, WTTC 2019). Consequently, big data-driven solutions can transform the tourism and hospitality sector and its allied services in the Indian market. Because the extant literature focuses largely on developed countries; however, the benefits of big data, the determinants influencing its adoption as well as its influence on firm performance in India are currently unknown. Furthermore, numerous works have also advocated that the firms'executives and senior officials have shown unwillingness during the transition to using big data analytics. It is critical that the senior officials and executives work towards managing and eventually overcoming these obstacles (social as well as environmental) and understand the need for data backed decisions. Limited studies are conducted on understanding if dimensions (factors) impact each other's impact since the dimensions (factors) are interrelated.

The current study aims to address these research gaps. It investigates the various determinants of BDA in tourism and hospitality firms as well as their cause-effect (CAE) relationships. We organised these determinants into three categories using the popular TOE theoretical framework. The three primary research questions (RQs) are as follows: (a) Which are the critical determinants in influencing the adoption of big data? (b) Which framework is best suited to investigate the determinants of big data adoption? (c) Do any relationships exist between the determinants influencing big data's adoption?

The present work employs a mixed-method sequential study design where researchers have used both qualitative and quantitative methods (Sharma, Gupta, and Acharya 2020c, 2020b). The qualitative study comprises semi-structured interviews and pairwise comparisons (quantitative) with 28 industry experts from three major OTAs. We analysed the data using MCDM methods, namely analytic hierarchy processing (AHP; Saaty 2008) followed by decision-making trial and evaluation laboratory (DEMATEL; Gabus and Fontela 1972). The study further utilised MCDM techniques to rank the BDA determinants and establish the CAE relationships between the variables.

After discussing the literature related to BDA & hospitality firms' performance in Section 2, we discuss the methodology in the next section, i.e. (Section 3). Subsequently, we discuss the analysis and results in Section 4. The research work provides a comprehensive summary in Section 5, and Section 6 outlines limitations & future research guidelines.

2. Literature review

Prior literature has emphasised that the application of big data to the tourism sector is foreseeable on three primary grounds. First, the tourism & hospitality sector is prone to various challenges, such as imbalances in the spending ways of tourists' due to seasonality, risky capital expenditures, and operational sensitivity (Kizildag et al. 2019; Karjaluoto et al. 2019). Big data can fundamentally improve a firm's marketing performance and data management (Verma, Bhattacharyya, and Kumar 2018), save effective costs, provide a competitive advantage and thus improve performance (Yadegaridehkordi et al. 2020).

2.1. Big data in hospitality

Tourism and hospitality firms generate enormous amounts of content (travel-related information) and utilise this data to serve their customers' growing demand (D. C. Wu, Song, and Shen 2017; Talwar et al. 2020a; Khanra, Dhir, and Mäntymäki 2020; Tandon et al., 2020). Meeting this demand becomes even more critical due to increasing requirements for competence and improved customer satisfaction (Sena et al. 2019; Akhtar et al. 2019; Yadegaridehkordi et al. 2020). Furthermore, to remain competitive and enjoy sustainable development, tourism and hospitality firms depend on the knowledge generated from big data (Back, von Krogh, and Enkel 2007; Sena et al. 2019; Akhtar et al. 2019; Khanra et al. 2021). Scholars thus argue that big data can revolutionise business (H. Li, Hu, and Li 2020) by allowing firms to understand consumers, market characteristics, competitors, the business environment, the influence of technologies and stakeholders more rationally (Xiang and Gretzel 2010; Nusair, Butt, and Nikhashemi 2019).

The prior tourism and hospitality literature on big data has primarily analysed consumers' searching behaviour, which includes customer value analysis (Hsieh 2009; Line et al. 2020) and customers' decisions when selecting a location (Chen and Tsai 2016) or purchasing airline tickets (Holland, Jacobs, and Klein 2016) as well as an expert system that provides recommendations for travel-related aggregators (Hsieh 2011; Kisilevich, Keim, and Rokach 2013) and machine learning techniques to assess trip objectives (Lu and Zhang 2015). Furthermore, scholars have explored how organisations can gain business intelligence (H. Li, Hu, and Li 2020) & improve their accomplishments by BDA (Akter et al. 2016; Sivarajah et al. 2017; Wamba et al. 2017). However, few works have explored big data's marketing, operational and strategic potential to enhance overall venture efficiency (Sheng, Amankwah-Amoah, and Wang 2017; Yadegaridehkordi et al. 2020).

Customer data assists hospitality firms in providing an inspirational, unique, authentic and easy experience to travellers (Yallop and Seraphin 2020). Among the significant impacts of big data are improved operational efficiency, reduced management risk and stronger customer relationships, which, in turn, produce a competitive advantage via efficient strategies for marketing and operations management (Sheng, Amankwah-Amoah, and Wang 2017).

Colleoni, Belk, and Llamas (2013) illustrated three important usages of social web data mining (word-of-mouth, detection of trends, effective networks) for applied research to capture social and behavioural dynamics. These perceptions are crucial to tourism and hospitality providers because they offer consumers an experience and predict the determinants of future purchases (Litvin, Goldsmith, and Pan 2018). Most BDA-related studies in this domain are based on data captured from social media (Kim and Tussyadiah 2013; Yallop and Seraphin 2020; Yadegaridehkordi et al. 2020). Big data and analytics are anticipated to influence Euromonitor International travel industry reports, in less than a decade (Bremmer 2019). However, BDA-related developments also have important consequences for issues, such as user privacy (Rivera 2020; Line et al. 2020; Sharma, Kamble, et al. 2021a; Sharma and Sehrawat 2020b).

Firms in hospitality sector must leverage their marketing and managerial strategies, tools and tactics (Sotiriadis 2017; M. Mariani et al. 2018; Sena et al., 2020) in order to advance from their competitors. A firm's performance value is directly proportional to the amount of resourceful information generated using big data (Mikalef, Boura, et al. 2019). Recent works have emphasised the reason firms should adopt big data and the ways in which this process can help them in the long term. For instance, M. Mariani et al. (2018) found that in the past decade, tourism firms have focused on client-centric needs, which principally value tourists' wants, needs, requirements and preferences. These travellers' needs are the primary factors in ensuring that travel choices improve customer satisfaction as well as the memorability and quality of the traveller experience. This focus allows firms to excel in a dynamic world where evolving consumer demands generate intense competition (M. Mariani and Baggio 2012). Big data is growing rapidly as a knowledge base, thus helping firms to capture the market by understanding consumer preferences.

Many industries are advancing in a fast-pace manner for utilising insights from big data analytics to develop critical insights and gain a competitive edge (Mikalef, Boura, et al. 2019). Benitez et al. (2019) demonstrated ways in which firms use IT-enabled OTAs to achieve an advantage by strengthening organisational capabilities, while Mikalef, Boura, et al. (2019) and Conboy et al. (2020) both proposed research models that elucidate the ways in which the adoption of big data analytics provides firms with dynamic marketing and technological capabilities and thereby improves the competitive performance of OTAs. However, a recent study noted that the potential of big data-related studies on OTAs in the tourism and hospitality sector has been insufficiently researched, underscoring the need for the present study (Nusair, Butt, and Nikhashemi 2019).

The literature has highlighted different adoption models, such as the diffusion of innovation (DOI) model; technology acceptance model (TAM); and the TOE-framework to study the adoption/diffusion of emerging innovations, such as cloud-computing (Sharma, Gupta, and Acharya 2020c, b); Industry 4.0 (Sharma, Sehrawat, et al. 2021b); blockchain (Clohessy, Acton, and Rogers 2019) and BDA (Yadegaridehkordi et al. 2020). Big data is a recent technological progression that calls for an in-depth analysis. Further, BDA is a multifaceted and intricate advancement hence it is not certain that existing adoption frameworks or models can do full justice in understanding the process (Chatterjee et al. 2021). The adoption of emerging technology is surrounded by a comprehensive list of determinants that fall under different categories, such as technology, environment and organisation. Further, it has been evident from the literature that the TOE frameworks (Tornatzky & Fleisher, 1990) has been used most extensively hence authors' resonate with previous works and utilised TOE. Further, especially in information systems (IS) research, TOE is also a widely utilised prominent framework (Sharma & Sehrawat, 2020a; Chatterjee et al. 2021). TOE is extremely popular on many accounts. It is a parsimonious IS specific framework which can reconnoitre and envisage the diffusion of numerous emerging innovations. TOE provides opportunity to explore comprehensive factors with different categories thereby exploring the technology adoption in a malleable way backed with strong theoretic and robust psychological measurements with nonpareil descriptive supremacy (Elghdban et al. 2020). Another critical feature of the TOE framework is its ability to provide holistic picture with extrinsic factors including environmental & societal characteristics (Awa, Nwibere, and Inyang 2010). TOE has explanatory power across several industrial, technological, & national cultural contexts (Elghdban et al. 2020) which can provide a holistic picture from all dimensions (Rosli, Yeow, and Siew 2012; Sharma and Sehrawat 2020a, 2020b). TOE is free from firm size and

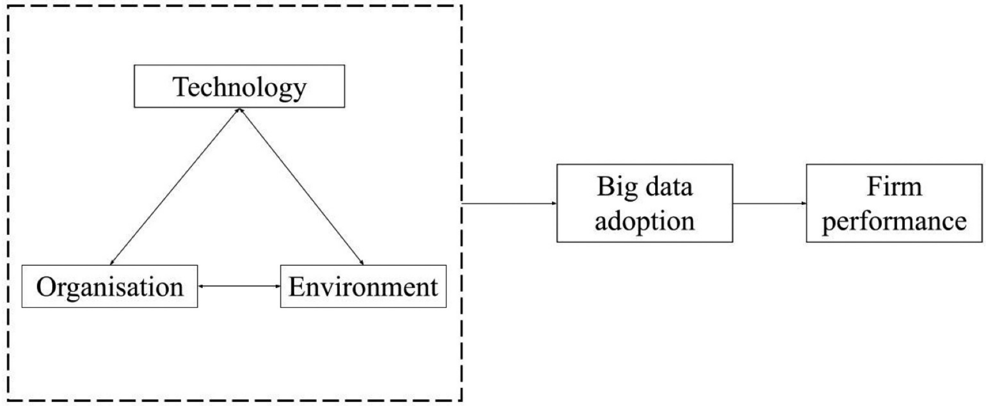

Figure 1. Conceptual framework.

industry restrictions, and it provides a clearer conceptualisation while exploring different factors under three dimensions (Jere & Ngidi, 2020). Figure 1 presents the conceptual framework proposed in the present work.

3. Research methodology

3.1. Method and data

This study employs a mixed-methods sequential research design (Creswell, Clark, and Garrett 2003) (see Figure 2). First, we shortlisted India's top 20 OTAs based on their annual reports and sent an email describing the study's objectives to these firms. After initial conversations, seven firms agreed to participate, and we sent these firms a semi-structured discussion guide. If the participants did not respond, we sent a gentle reminder after 15 days. If, after four reminders, an OTA participant still did not answer, we sent no additional reminders. Finally, we organised qualitative interviews with 25 experts from the three OTAs to investigate the determinants of BDA and categorise them using the TOE-framework (Hennink et al., 2017). The interview inquiries aligned with the research questions. We also asked the participants for their feedback, which we incorporated into the subsequent rounds for other participants. We then conducted a quantitative study to rank the determinants using AHP (Sharma, Gupta, and Acharya 2020c, 2020b) and identify their interactions and dependencies using DEMATEL[1] (Gabus and Fontela 1972, 1973). The application of MCDM techniques to firm decision-making issues is flourishing because of the distinctive method of ranking all the potential alternatives and computing their relative weights (Yasmin et al. 2020). MCDM assist in selecting an optimal outcome among the existing choices (Taha and Rostam 2012). The analytic hierarchy process (AHP) method has been extensively utilised in numerous industries to prioritise the choices using weights obtained from the professionals (Saaty, 1980). In the AHP, a hierarchy cogitates (objective) goal's distribution among the alternatives being equated and ranked based on the comparative impact on that objective. The DEMATEL technique can check interdependence among alternatives

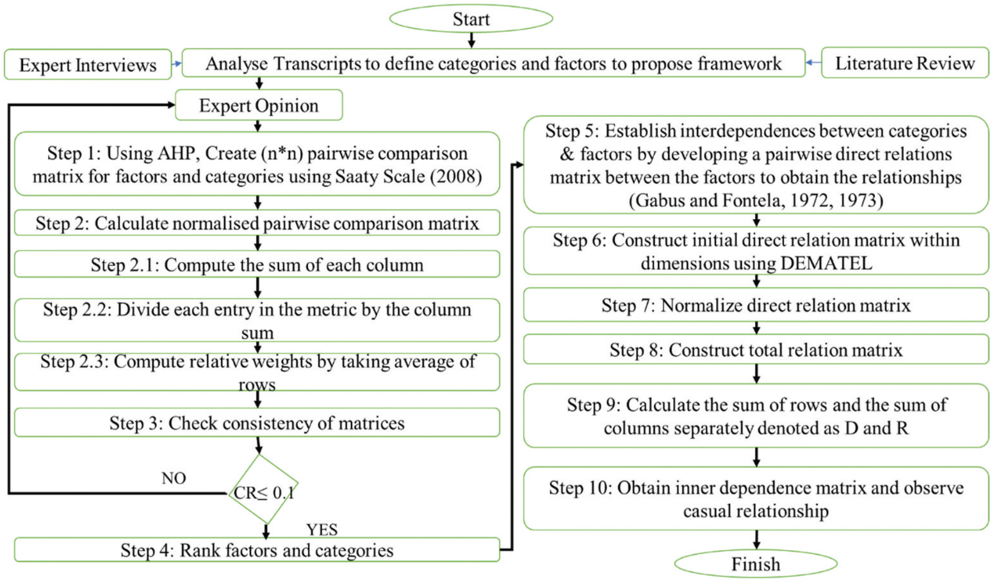

Figure 2. Overview of the methodology followed.

and reflect their relative relationships that can be used for inspecting and solving intertwined and complicated problem areas (Sharma et al., 2021b). DEMATEL meritoriously analyses the mutual influences (both direct and indirect effects) among diverse alternatives and comprehends the intricate cause and effect relations. The DEMATEL is utilised not only to decide the alternatives' ranking but also to compute the evaluation criteria and measure their weights. Hence, we collected the data for AHP using the priority matrix for ranking the determinants and related categories (Saaty 2008) before applying DEMATEL to establish the causality between the determinants (Gabus and Fontela 1972). The 'directed graphs' present the directed relationships among the determinants.

We chose the OTAs and their experts based on the following criteria: (a) the OTAs must be well-established, innovative and technology- and data-driven, and they must have adopted big data analytics; (b) the firms must be willing to share information and provide time for the researchers to conduct three to four rounds of interviews; (c) the firms must desire to provide feedback on the research results and proactively assess whether the determinants actually help them to improve firm performance; (d) the participating experts must possess in-depth knowledge and experience in IT and in the tourism & hospitality sector (see Table 1). The authors utilised alumni networks and platforms such as social-media (Facebook, Twitter and LinkedIn) to connect with and recruit industry experts. They conducted multiple rounds of interviews (3–4 h at a time) from November 2019 to March 2020 in the English language.

We transcribed and analysed the collected data using axial coding to map the relevant determinants with the literature. A total of seven managers and 21 executives from three OTAs participated in the study. Before the actual study, we assured the participants that we would maintain their confidentiality and anonymity in the

Table 1. Firms and respondents' profile.

S. No	Firm	Size of the firm (no. of employees)	Revenue (millions)	No. of managers interviewed (Designations)	No. of executives interviewed (experience > 5 years and age < 32)	Year of big data adoption
1	C1	3051	675 (2017)	2 (> 10 years of experience; 1 Senior IT Analyst, 1 Senior Project Manager)	7 (3 Female, 4 Male)	2016
2	C2	1388	600 (2015)	2 (> 14 years of experience; 1 Senior Director, 1 Director)	8 (2 Female, 6 Male)	2016
3	C3	4000	330 (2018)	2 (> 7 years of experience; 1 Big Data Analyst, 1 Associate Director)	6 (3 Female, 3 Male)	2018

Note: C: Company (C1: Company 1, C2: Company 2, C3: Company 3); Background of Manager: Designation (Gender, Age, Qualification); Senior IT Analyst (Female, 38, Graduate); Senior Project Manager (Male, 45, Postgraduate); Senior Director (Male, 51, Doctorate); Director (Male, 50, Postgraduate); Big Data Analyst (Female, 32, Postgraduate); Associate Director (Male, 33, Postgraduate).

collected data. Consistent with this agreement, we have not disclosed the identities of the participants or their firms in this article. Table 1 presents the profile of the participants and their firms.

3.2. *Qualitative analysis*

We utilised content analysis to develop codes from the interview transcript content. These codes were categorised and counted to determine the frequency with which they occurred. Similar codes were then categorised under one determinant (P. Sun, Cardenas, and Harrill 2016). We analysed all transcripts using a three-step coding process as follows: (a) transcripts were read carefully, and coding was completed based on the frequency of the words or phrases; (b) similar codes were assigned under one determinant; (c) determinants were grouped into three categories of the TOE framework. Table 2 presents sample transcripts to describe the process used for the analysis. Table 3 defines the determinants that were shortlisted based on a comprehensive literature review (Vidgen, Shaw, and Grant 2017; Mikalef, van de Wetering, and Krogstie 2020; Maroufkhani et al. 2020). Figure 3 presents the TOE framework and determinants.

3.3. *Quantitative analysis*

3.3.1.1. *Analytic Hierarchy Processing (AHP)*

We executed the AHP process step by step to rank the identified determinants of BDA (Saaty 2008). Furthermore, we assessed the data's consistency by calculating the consistency index (less than 0.1; Sharma & Sehrawat, 2020b). If any discrepancies appeared in the data, we conferred again with the experts. Table 4 elaborates on the individual and combined rankings for all organisations.

3.3.2. *Dematel*

We conducted a DEMATEL analysis on the collected data using a scale of 0–4 (0: No effect–4: Very high effect) to identify the relationships among the three categories of determinants (technological, organisational and environmental). First, we computed

Table 2. Sample transcripts.

Statement (Participant designation, age)	Code	Determinants
'There is always a need for people with excellence who have expertise in managing, controlling and processing IT software'. (Senior IT Analyst, 38)	Expertise in IT software	Prior IT experience
'We need people who know how to judiciously use the information extracted from the huge amount of data. With the right quality of people, a firm can manage to perform well and excel in their competencies'. (Associate Director, 44)	Quality and competency	Human resource capability
'While making a decision of whether we should use findings from massive data, the two things that we consider first are quality and cost'. (Big Data Analyst, 30)	Quality and cost	Big data quality; perceived costs
'It's actually very, very difficult to predict how the initial investment will benefit in the future. Being a start-up, we need to invest wisely, so initially, we adopted it [big data] for a particular project to see if we can actually achieve what we expect'. (Senior Project Manager, 32)	Adoption on a project basis	Trialability

the initial direct relation matrix. In this step, we also computed the direct primary effects of one determinant on the others. Table 5 shows the initial and total influence matrix. $R_i + D_j$ and $R_i - D_j$ values present the intensity of the relationships as well as the relational influence between each factor, as shown in Table 6. The causal factor is denoted by $R - D > 0$, while the effect factor is denoted by $R - D < 0$.

4. Results

Seventeen determinants, which were found to be consistent with the prior literature, were classified into three categories (see Table 3). The technology category consists

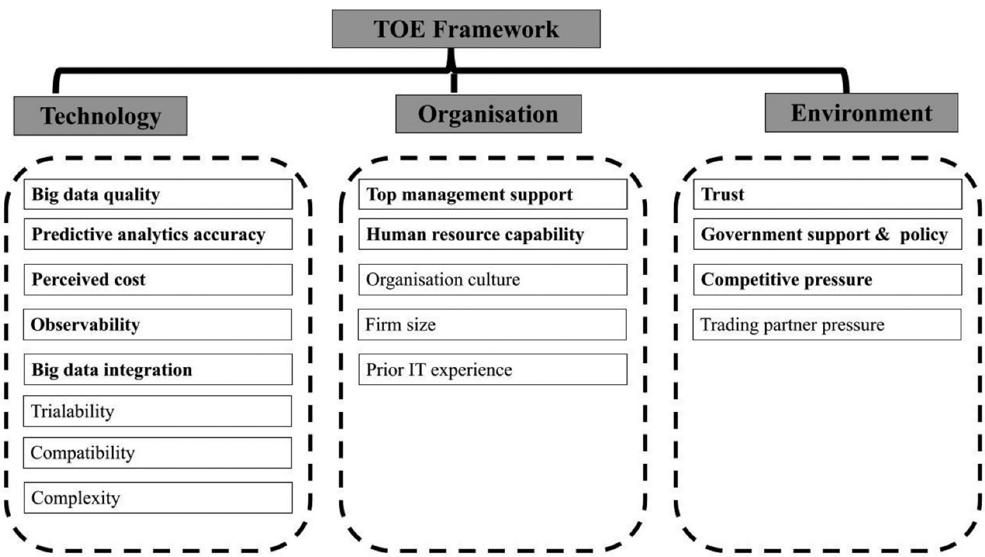

Figure 3. TOE framework determinants for big data adoption. Note: Determinants in bold represent critical (top 10) determinants revealed from AHP.

Table 3. Determinants influencing big data adoption by hospitality firms.

Framework (categories)	Determinants	Definition	Source of definition
Technology	Big data integration	Data integration is a set of procedures applied to recover and blend data into valuable and meaningful information from distinct sources. It delivers trustworthy data from an assortment of sources.	Yadegaridehkordi et al. (2018)
	Big data quality	Big data quality has two central dimensions: data consistency and data completeness. Well-managed and clean data ensures quality and reliable information and encourages its strategic and tactical usage.	Kwon, Lee, and Shin (2014)
	Compatibility	The attributes of big data are coherent with the contemporary IT structural design (e.g. integration into the existing IT systems, scalability).	S. B. Park, Ok, and Chae (2015)
	Complexity	Initially, big data is perceived to be rather challenging to comprehend and apply (e.g. difficulties in learning-related expertise).	Yadegaridehkordi et al. (2018)
	Observability	Firms acknowledge the benefits of big data after monitoring how other organisations (usually innovators) utilise it.	Yadegaridehkordi et al. (2018)
	Predictive analytics accuracy	Predictive analytics is the procedure of extricating information from available datasets to ascertain patterns and predict future trends. The precision and exactitude of the information are critical to making accurate predictions about future or otherwise unknown events.	Soon, Lee, and Boursier (2016)
	Perceived costs	Perceived costs are potential expenditures related to big data adoption (such as the substantial preliminary investment needed to embrace the adoption of big data, costs of applying big data technology, etc.).	Nam, Kang, and Kim (2015); Yallop and Seraphin (2020)
	Trialability	Senior management generally adopts big data without complete commitment (i.e. trying with minimum financing).	P. Sun, Cardenas, and Harrill (2016)
Organisation	Organisational culture	Organisational culture is the culture of a firm that promotes suggestions, opinions and expressions regarding the methods and procedures. The awareness of commitment to knowledge transfer and integration within a firm.	Brok and Khan (2017)
	Human resource capability	The organisational resources (i.e. human) are suitable for the mission of big data adoption (e.g. statistics scientists, analysts, experts, data scientists).	Soon, Lee, and Boursier (2016)
	Firm size	Firm size is the annual income/turnover/returns and count of personnel that support big data adoption in a firm (e.g. corporations with larger turnovers/ returns).	P. Sun, Cardenas, and Harrill (2016)
	Prior IT experience	Prior IT experience refers to the firm's experience of working with IT and related projects.	Kwon, Lee, and Shin (2014)
	Top management support	Leaders are prepared to assign adequate resources and support the initial big data adoption (e.g. CIOs' and CTO's willingness to adapt).	Brock and Khan (2017)
Environment	Competitive pressure	The magnitude of the pressure from a firm's competitors can be tackled using big data adoption (e.g. external risks from competitors, competitive market).	S. B. Park, Ok, and Chae (2015)
	Trading partner pressure	Firms adopt big data to have good relations with partners and retain internal balance (e.g. the enthusiasm of suppliers in external partnerships).	Nam, Kang, and Kim (2015)
	Government support and policy	Governmental bodies encourage organisations to adopt big data by offering legal support.	Nam, Kang, and Kim (2015)
	Trust	The organisation's belief that it will be secure while/ after adopting big data (e.g. inter-organisational trust, safeguard to system trust, reliable platform, reliability, trust and strong relationship).	Yadegaridehkordi et al. (2018)

Note: CIO-chief information officer; CTO- chief technology officer.

Table 4. Ranking of factors influencing big data adoption using the AHP.

Category	F1	F2	F3	GM (a)	Determinants	F1	F2	F3	GM (b)	a*b	Rank
Technology	0.6	0.7	0.33	0.51	Big data quality	0.2	0.25	0.15	0.195	0.101	1
					Predictive analytics accuracy	0.2	0.25	0.05	0.135	0.070	4
					Trialability	0.1	0.05	0.07	0.070	0.036	11
					Complexity	0.1	0.1	0.03	0.066	0.034	12
					Observability	0.1	0.1	0.06	0.084	0.043	8
					Big data integration	0.1	0.1	0.04	0.073	0.038	9
					Perceived costs	0.1	0.1	0.08	0.092	0.048	6
					Compatibility	0.1	0.05	0.02	0.046	0.024	16
Organisation	0.2	0.2	0.33	0.23	Organisational culture	0.2	0.1	0.15	0.144	0.034	13
					Prior IT experience	0.1	0.1	0.15	0.114	0.027	15
					Top management support	0.3	0.4	0.3	0.330	0.078	3
					Firm size	0.2	0.1	0.15	0.144	0.034	14
					Human resource capability	0.2	0.3	0.25	0.246	0.058	5
Environment	0.2	0.1	0.33	0.18	Competitive pressure	0.15	0.2	0.25	0.195	0.036	10
					Trading partner pressure	0.15	0.1	0.05	0.090	0.017	17
					Government support and policy	0.3	0.25	0.2	0.246	0.046	7
					Trust	0.4	0.45	0.5	0.448	0.084	2

Notes: F1: Firm 1; F2: Firm 2; F3: Firm 3; GM: Geometric Mean.

of eight determinants (*big data quality, predictive analytics accuracy, trialability, complexity, observability, big data integration, perceived costs, compatibility*). Meanwhile, the organisation category includes five determinants (*organisational culture, prior IT experience, top management support, firm size, human resource capability*). Finally, the environment category consists of four determinants (*competitive pressure, trading partner pressure, government support and policy, trust*).

4.1. Ranking and association among categories

We employed AHP and DEMATEL to determine the ranking and association among categories and determinants, respectively. The AHP final ranking indicates that *technology* is the *most crucial category* influencing BDA, followed by organisation and environment (refer to Table 4). Tables 6 and 4 indicate that *technology* and *organisation* are *critical categories* influencing a firm's BDA and performance. *Technology* (R – D = 1.05) is also positioned in the *cause* group (CG), suggesting its influence on BDA, while *organisation* and *environment* fall into the *effect* group (EG), as shown in Table 6.

The *organisation* category ranks *second* based on the AHP analysis (see Table 4) and is positioned in the *EG* (see Table 6). The *environment* dimension (global weight = 0.18) holds the *third* position (see Table 4). Moreover, it falls into the *EG* (see Table 6), with a (R – D) score of −0.912. Figure 4, which was formed by analysing the data from the total influence matrix (see Table 5), presents a detailed framework for BDA in tourism & hospitality firms. It further elucidates the relationships among categories, their influence on big data and, finally, its effect on firm-performance. All three firms experienced a percentage increase in revenue following their adoption of big data. Firm 1 and Firm 2 witnessed an increase of 1.5% and 2% (Jan – March 2019), respectively, while Firm 3 had a substantial increase of over 3.5% (Jan – March 2019).

Table 5. Expert's view and total influence matrix for technology-organisation and environment (DEMATEL).

Category	Environment	Organisation	Technology
Expert's view (data collection)			
Environment	0	4	3
Organisation	3	0	2
Technology	1	1	0
Total influence matrix			
Environment	0.590	1.048	0.982
Organisation	0.779	0.556	0.779
Technology	0.339	0.372	0.252

4.2. Ranking and association among determinants

We ranked the determinants according to the priority the experts assigned to them. Under each category, the most critical determinants are *big data quality* followed by *predictive analytics accuracy* (under technology), *top management support* and *human resource capability* (under organisation) & *trust* and *government support and policy* (under environment).

We also utilised DEMATEL to rank the determinants under each category, as shown in Table 6. *Big data quality*, *predictive analytics accuracy*, *perceived cost* and *big data integration* hold the top four positions, respectively, in the *technological* category. Furthermore, all four determinants with (R – D) scores of 0.124, 0.123, 0.045 and 0, respectively, belong to the cause group, indicating their influence on determinants in the *EG*. The *EG* consists of the determinants of *observability, complexity, compatibility* and *trialability*, with (R – D) values of −0.003, −0.024, −0.075 and −0.19, respectively.

Within the *organisation* category, we arranged five determinants according to their relative importance as follows: *top management support* > *human resources capability* > *organisational culture* > *firm size* > *prior IT experience* (see Table 4). *Top management support* and *human resources capability* are third and fifth, respectively, in the global ranking (see Table 4). *Prior IT experience* lies in the *EG*, while all other determinants lie in the cause group. Thus, it is necessary to accentuate the determinants in the cause group, which, in turn, influence the *EG* determinants.

The four determinants under the *environment* category ranked in the following order: *trust* > *government support and policy* > *competitive pressure* > *trading partner pressure* (see Table 4). *Trust* also placed second with a global weight of 0.08406118, confirming it as one of the most important determinants in firms' big data adoption. Moreover, it belongs to the cause group with an (R – D) score of 0.884. Further, government support and policy and competitive pressure also belong to the *cause* group, while *trading partner pressure* falls into the *EG* (see Table 6). The analysis also emphasises that decision-makers are alarmed regarding the quality and accuracy of big data and rely on trust and support from management when deciding to adopt big data to enhance their business.

In summary, the DEMATEL outcomes indicate that the *technology* category has the most substantial effect on organisational and environmental determinants. Indeed, the *technology* and *organisation* categories are more significant than the *environment* category. Meanwhile, determinants in each category were also ranked, with the following as the most critical: technology—(cause factors) *big data quality*, *predictive analytics*

Table 6. DEMATEL ranking and cause-effect relationship for categories and determinants.

Category (determinants)	D	R	D+R	R-D	CR and LR	Cause-Effect
Technology	0.963	2.013	2.976	1.050	1	Cause
Big data quality	1.245	1.170	2.415	−0.075	7	Effect
Predictive analytics accuracy	1.345	1.155	2.500	−0.19	8	Effect
Trialability	1.373	1.349	2.722	−0.024	6	Effect
Complexity	1.630	1.753	3.383	0.123	2	Cause
Observability	1.497	1.621	3.118	0.124	1	Cause
Big data integration	2.458	2.455	4.913	−0.003	5	Effect
Perceived costs	1.336	1.381	2.717	0.045	3	Cause
Compatibility	1.707	1.707	3.414	0	4	Cause
Organisation	2.114	1.976	4.090	−0.138	2	Effect
Organisational culture	2.176	2.365	4.541	0.189	3	Cause
Prior IT experience	1.858	2.027	3.885	0.169	4	Cause
Top management support	3.239	1.805	5.044	−1.434	5	Effect
Firm size	1.823	2.177	4.00	0.354	2	Cause
Human resource capability	2.328	3.050	5.378	0.722	1	Cause
Environment	2.620	1.708	4.328	−0.912	3	Effect
Competitive pressure	1.293	2.177	3.47	0.884	1	Cause
Trading partner pressure	1.522	2.146	3.668	0.624	3	Cause
Government support and policy	1.649	2.286	3.935	0.637	2	Cause
Trust	2.557	0.412	2.969	−2.145	4	Effect

Note: R: Sum of Rows; D: Sum of Columns; CR: Category Rank; LR: Local Rank of Determinants (under each category).

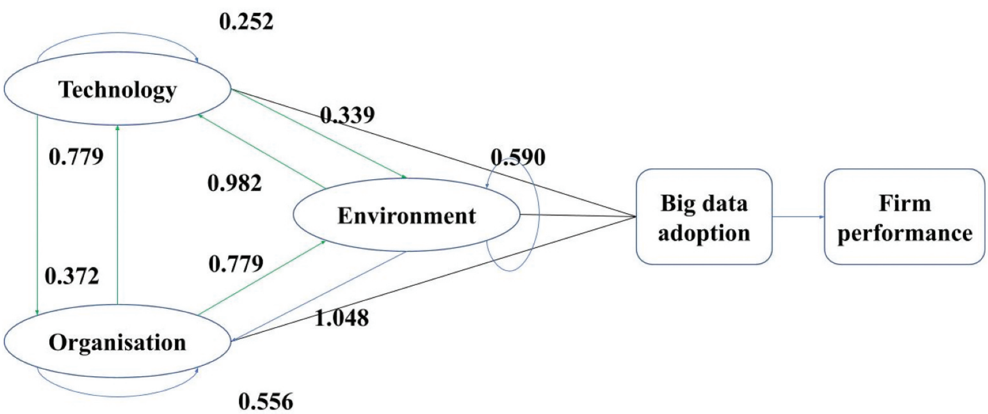

Figure 4. Total influence map for technology, organisation and environment influencing big-data-adoption and firm's performance in Indian hospitality firms. Note: Green arrow shows the degree of relative impact between categories; blue arrow shows net influence on a category; black arrow shows the influence of technology-organisation-environment on BDA; purple arrow shows the impact of BDA on firms' performance.

accuracy, *perceived costs*, *big data integration*, (effect factors) *observability*, *trialability*, *complexity*, *compatibility*; organisation—(cause factors) *top management support*, *human resources capability*, *organisational culture*, *firm size*, (effect factors) *prior IT experience*; environment—(cause factors) *trust*, *government support and policy*, *competitive pressure*, (effect factors) *trading partner pressure*.

5. Discussion

This study addressed **RQ1** by examining the determinants and their criticality in influencing the BDA. We identified 17 predictors of BDA and classified them into three categories of the TOE framework. Technological innovation can be fully utilised only when there is assistance from assorted assets within the firm. The organisation category involves the environment, resources, & features that help in the acceptance or dismissal of emerging technologies. Further, the environmental category demonstrated organisation's extrinsic environment may pose stress and non-cooperative attitude that have a direct influence on the member of staff's advancement as well as business environment. While the prior literature has examined these possible determinants, it has not yet explored them from the perspective of technology, organisation and environment, specifically in the tourism & hospitality sector in the context of BDA (S. B. Park, Ok, and Chae 2015; S. Park et al. 2020; Yadegaridehkordi et al. 2018).

Technology is an influential category for BDA (J. Li et al. 2018; H. Li, Hu, and Li 2020), as the use of big data significantly depends on technologies for investigating massive volumes of information (Yadegaridehkordi et al. 2020). The determinants categorised under this dimension are as follows: 'big data quality, 'predictive analytics accuracy', 'trialability', 'complexity', 'observability', 'big data integration', 'perceived costs' and 'compatibility'. Firms need to employ specialists and possess requisite infrastructure beforehand since it will help in achieving better accuracy and easy integration. Further, in line with previous research in the same domain (BDA) by Baig, Shuib, and Yadegaridehkordi (2019) it has been found that risk, uncertainty, and high cost, are constantly connected with complexity.

Organisation is another category with an influential role in predicting BDA (Yadegaridehkordi et al. 2018). However, the literature has largely overlooked this perspective, especially in the domain of tourism & hospitality (Yadegaridehkordi et al. 2020). Adopting an IT innovation, such as CC, blockchain and big data, can significantly transform a firm's internal and external processes (Clohessy and Acton 2019; Sharma and Sehrawat 2021). Because they cannot predict the possible consequences, organisations thus exercise caution when deciding to adopt innovations. Consistent with the findings of previous work (P. Sun, Cardenas, and Harrill 2016), the organisational determinants included in this study are 'human resource capability', 'top management support (TMS)', 'firm size', 'organisational culture' and 'prior IT experience'. One of the most critical point is that if any firm lacks TMS, it becomes reluctant to transform and accept changes which will delay the overall the process of adoption. TMS is essential to design and implement rules, guidelines as well as enjoying financial independence before making any critical decision (Baig, Shuib, and Yadegaridehkordi 2019).

Factors in the e*nvironment* category also act as influential predictors in adoption of emerging technology, including CC (Sharma, Gupta, and Acharya 2020a) and blockchain (Clohessy and Acton 2019). Determinants under this category are 'competitive pressure', government support and policy', 'trading partner pressure' & 'trust'. The firms who have already adopted innovations have an edge over players who are entering comparatively late in the market. Hence, technological innovations need immediate attention to not only capture the wider market but also to decrease the pressure from competitors.

To answer **RQ2**, the authors ranked the determinants and their categories to identify the most critical of each.

Technology is the most influential category, followed by *organisation* and *environment*. Furthermore, the AHP technique revealed that the five most critical determinants for BDA in hospitality firms are *big data quality, trust, top management support, predictive analytics accuracy* and *human resource capability*. Prior studies have discussed these factors independently (Akhtar et al. 2019; Sena et al. 2019). However, the present study is the first empirical work in the tourism & hospitality context that provides a thorough list of ranked determinants of BDA.

Big data quality and *predictive analytics* are critical determinants for understanding tourist behaviour and for segmenting repeat visitors. For example, firms can utilise technology-related determinants to recommend specific packages to travellers that will promote goodwill among customers and increase firm performance. While big data in this sector is sufficient in terms of volume, it is usually suppressed by quality problems (J. Li et al. 2018). Concerns regarding the reliability of online data cannot be overlooked because some consumers may provide counterfeit reviews (Amadio and Procaccino 2016; J. Li et al. 2018). Similarly, due to approximation methods and problematic data sampling, data from Google trends may be biased (J. Li et al. 2018). Consequently, *data quality* is crucial for making informed decisions, and *big data quality* is critical in helping firms make informed decisions and actions based on correct, reliable and complete data. Furthermore, quality data helps firms identify and remove insignificant information characterised by errors and missing values (Ardagna et al. 2018).

Trust and *top management support* are also influential factors in adopting emerging technologies, such as CC (Sharma and Sehrawat 2020a; Sharma, Gupta, and Acharya 2020b, 2020c) and Industry 4.0 (Sharma, Kamble et al., 2021a). Similarly, *trust* is important in the hospitality context where client data is sensitive and any breach can lead to a loss of business and severely harm the firm's brand image.

Top management support holds utmost importance in terms of adoption determinants in the organisation category (Brock and Khan 2017). The requisite role of senior managers in granting funds and creating a positive firm environment can drastically accelerate innovation implementation (Sharma, Gupta, and Acharya 2020c, 2020a). Frisk and Bannister (2017) confirmed that managers' collaboration and contribution can accelerate BDA (S. B. Park, Ok, and Chae 2015; S. Park et al. 2020).

Furthermore, the final decision to adopt or reject any emerging technology depends on senior officials' opinion about that technology (Akter et al. 2016; Sharma, Gupta, and Acharya 2020c). The present work reveals that firms expect *high data quality* and *predictive accuracy* with only marginal investments. However, the present work also indicates that firms focus more on *trust and policies* for BDA. This also implies the need to rely on previous theories when understanding the adoption of any innovation because the magnitude of influence for each criterion/determinant might vary substantially with the sector, geography and industry.

Human resource capability is another critical determinant in a firm's decision to adopt any innovation. A firm has two primary requirements: a) sufficient human capability for the progression and b) the degree to which adherents are behaviourally and psychologically equipped to implement organisational transformation (Sharma, Gupta, and Acharya 2020a; Yadegaridehkordi et al. 2020). Although the introduction of big data offers benefits, human capability and readiness for its adoption are critical for firms to enjoy these advantages to the fullest (P. Sun, Cardenas, and Harrill 2016).

Consistent with Xu, Nash, and Whitmarsh (2020), *perceived cost* ranks sixth in the present research. The cost of data collection can become a major deterrent for big data and tourism research. Indeed, this data collection requires a high initial investment to purchase devices (e.g. GPS loggers and Bluetooth sensors) and recruit volunteers. However, web search data has a comparatively lower cost and significant application in tourism research (J. Li et al. 2018). Big data offers substantial benefits to businesses in enhancing decision-making, generating revenue, managing risk and reducing cost (Shin 2015). We posit, however, that firms struggle to invest significantly in the resources and time required for big data's fruitful implementation. The main reason firms delay adopting big data is that the returns from the predictions generated by big data are unclear. The data can only predict the 'what' aspect of decision-making while completely ignoring the 'how' and 'why'. This study's findings also confirm the other two factors, *observability* and *trialability*, as essential factors for BDA. However, they ranked eighth and eleventh, respectively. While these factors are extremely critical in other sectors, such as IT and academia (Gangwar, Date, and Ramaswamy 2015), in the context of big data in hospitality firms, they are thus outranked by other factors that are more decisive for its adoption.

As previous studies have shown, *compatibility* and *complexity* do not rank among the top 10 factors (Sharma, Gupta, and Acharya 2020b; Yadegaridehkordi et al. 2020). The literature has emphasised *firm size* as an essential factor influencing IT innovation implementation (P. Sun, Cardenas, and Harrill 2016; Sharma, Gupta, and Acharya 2020a; Yadegaridehkordi et al. 2020), and it was, therefore, anticipated also to impact the perceived value of big data. However, *firm size* did not rank in the top 10 factors, while *prior IT experience* placed 15th. Moreover, previous hospitality-related studies identify these factors are crucial for BDA (Sena et al. 2019; Yadegaridehkordi et al. 2020). These results contrast with two environmental factors (*pressure from 'trading partners'* and '*competitors'*), which are important in predicting IT adoption (Gangwar, Date, and Ramaswamy 2015; Leung 2020; Yadegaridehkordi et al. 2020). Furthermore, *government support and policy* influence the innovation adoption, such as CC (Sharma et al., 2020b, 2020c) and blockchain (Clohessy and Acton 2019; Sharma, Sehrawat, et al. 2021b) in various sectors, such as manufacturing (Yadegaridehkordi et al. 2018) and healthcare (Sharma and Sehrawat 2020a). However, its influence has not yet been explored in the tourism and hospitality domain (Yadegaridehkordi et al. 2020).

The AHP rankings are the best way that allows prospective adopters to understand the offerings of big data. AHP scores assess the strength of alternative choices relative to the best ones. The results thus help policy and decision-makers to understand the potential of BDA to improve a firm's performance. For big data service providers, the present study recommends building trust with all big data stakeholders. Providers can also differentiate among prospective big data users based on the determinants recognised in this study. *Big data quality* and *predictive analytics accuracy* are critical determinants in a firm's efforts to generate greater business benefits. Tourism and hospitality firms are advised to develop strategic procedures that rely on the significance of the adoption determinants and their interrelationships while choosing a suitable big data service provider. Meanwhile, government bodies are encouraged to establish proper policies and measures to foster trust in and loyalty to hospitality firms. Although a few factors are more critical than others, management and strategy decisions should consider all factors (Behl et al. 2019). It may also be essential to allocate separate teams to explore each perspective's working strategies. Thus, we recommend that service providers offer well-recognised and trusted services with suitable attributes after judicious consideration of the highest ranking factors under each category.

Finally, to answer RQ3, the authors examined the CAE relationships between the determinants of BDA. The present study's findings centre on the ontological integration of the determinants. This viewpoint acknowledges the deep interconnections among the technological, organisational and environmental dimensions, which hinder efforts to gauge their individual contributions (Akter et al. 2016). This conceptualisation thus emphasises that these dimensions act together and influence one another.

This is a critical aspect of the present research because no existing study in the tourism domain has categorised factors into CAE groups. This study, however, places technology in the CG while organisation and environment are in the EG. This is crucial for firms because the influence of technology offers a new and competitive perspective (Yadegaridehkordi et al. 2020).

Big data quality, predictive analytics accuracy, perceived costs, big data integration, top management support, human resource capability, organisational culture, firm size, trust, government support & policy and *competitive pressure* are critical factors for firm performance. The first two determinants help transform data into insights, thereby improving a firm's business growth and productivity (Akter et al. 2016). The findings align with Court (2015), who highlighted that organisations can increase their operating margins by 60% by adopting big data analytics efficiently. Furthermore, big data integration helps firms continuously reconfigure resources and integrate big data into trustworthy information. The proper alignment between business performance and BDA depends on the goals and objectives of leadership.

5.1. Theoretical implications

This work proffers three vital academic contributions. First, big data and its adoption will facilitate a long-term societal transformation. This technological transformation, in turn, will produce a significant impact on societal dynamics. Organisations must thus make informed decisions based on extensive research into both the pros and cons of technology and in-depth knowledge regarding the factors that serve as actuators for firm performance. Prior literature lacks clear knowledge regarding the possible determinants of BDA and their influence on firms performance, i.e. achieving significant profits and obtaining a competitive advantage in the market. The current study bridges this gap by providing a comprehensive list of categories and determinants influencing BDA and firm performance. The study first identified, categorised and ranked the determinants and later established the causality between them. These findings are important for tourism and hospitality firms as they continue to undergo a massive technological transformation.

Second, this research confirms that the proper exploitation of digital data facilitates efforts to monitor and identify trends in customer behaviours. Such trends involve the amalgamation of different dimensions. The present work extends the expertise of the existing big data literature by utilising the TOE framework and thus bridges the theoretical lacuna with this integrated methodology by employing an underlying framework in the context of big data. While TOE has been used in various sectors, such as manufacturing (Yadegaridehkordi et al. 2018; Sharma and Sehrawat 2020b) and information technology (Verma, Bhattacharyya, and Kumar 2018), it has not been fully explored in the tourism domain (Yadegaridehkordi et al. 2020). Moreover, no prior research has examined such an extensive list of determinants. The current research provides the extant literature, with an overarching theoretical foundation using the TOE framework.

Third, the current study utilised mixed-methods research comprising in-depth interviews followed by MCDM methods, thereby offering a comprehensive conspectus of the determinants (i.e. actuators and impediments) for adoption of big data. This mixed-methods research methodology was required to answer the study's RQs, i.e. to find, prioritise & examine the CAE relations among the determinants. The research methodology varies from those of former works, which have primarily employed qualitative methodology (S. Sun et al. 2018) and cross-sectional surveys (Mikalef, van de Wetering, and Krogstie 2020). The present research method can aid future researchers to have a holistic comprehension of the various factors influencing the adoption of disruptive technologies, such as blockchain, CC and artificial intelliegence.

5.2. Managerial implications

This research entails three vital practical inferences for big data tourism & hospitality firms, policymakers and service providers. First, the tourism & hospitality sector are often depicted as conservative, with low tolerance to disruptions and impervious to embracing emerging technologies (Filimonau and Naumova 2019). Even as the implementation of big data becomes inevitable, therefore, the tourism and hospitality sector remain reluctant to reconnoitre the potential of big data to inform profitable outcomes. Filimonau and Naumova (2019) also emphasised that the novelty of big data poses a challenge to its ubiquitous adoption in businesses. Hence, the present research work provides scrupulous knowledge and detailed investigation with a eclectic list of critical determinants of BDA while identifying the specific determinants that can positively influence firm performance. Furthermore, the current study provides insights into the ranking of these determinants as well as the CAE relations among them, the categories and firm performance. This kind of knowledge and understanding offers significant value to firms and managers by enabling them to prioritise the most influential variables that can significantly enhance their business potential. It is also worth noting that the organisations that adopt big data are most-likely to enjoy the first-mover benefit.

Second, the analysis suggests that the technology variables, namely big data quality & predictive analytics accuracy, are critical determinants of both BDA and firm performance. These variables collectively provide data-driven results, which enable management decision-making to cater to travellers' demand and enhance customer engagement and satisfaction (Lan et al. 2016; Mikalef, van de Wetering, and Krogstie 2020). Scholars have also perceived that the speed with which tourism and hospitality firms adopt technologies that disrupts the market regulates their business economic-growth (Law, Buhalis, and Cobanoglu 2014). Consequently, firms and managers should remain cognisant of the potential of both data quality and predictive accuracy to make or break their businesses. For example, in the context of popular tourist destinations in 'high' seasons, these factors could help firms avoid consumer dissatisfaction and encourage business reciprocity, thereby enhancing firm performance.

Third, the study's findings highlight *trust* and *government support & policy* as key variables in the context of the environment for attaining early adoption followed by the rapid diffusion of emerging innovations (Sharma & Sehrawat et al., 2021), such as big data, particularly if there is involvement of consumer-related information. It is critical to note that trust is mandatory for both consumers as well as regulators otherwise the organisation has high chances of facing pushback in the market. Consumers cannot trust any firm with their data especially when the firm even does not know how the data might be utilised in the imminent years. Moreover, scholars argue that BDA remains in its nascent stages primarily due to the lack of diligent government provision and policy-making (Pencheva, Esteve, and Mikhaylov 2020). Thus, the authors suggest that (a) governments articulate suitable policies to regulate the BDA, and (b) organisations establish a proper structure for dynamic processes and teams with matching data skills and governance policy. It is the need of the hour that a governing body or council should be set up to make sure that appropriate information governance processes are implemented in a timely manner.

Fourth, the decisions backed with big data gives firms in different sectors a prospect to transcend contenders. The BDA may require initial investment; however, the returns are multi-folds.

5.3. Social implications

First, this study's findings highlight the need for governments across the globe to propose and implement policies to reduce the digital divide and enhance standardisation, especially because no clear policy currently exists regarding digital rights. The 'Council of Big Data Ethics' and society must establish a fundamental foundation for data transparency. Individuals have different expectations for privacy; hence, robust regulations and risk mitigations must accompany efforts to share sensitive datasets.

Second, digital infrastructures act as inception points for increasing the possibilities of observation and management. User profiles and related information can be closely scrutinised, assessed and approved much more clearly. There is an urgent need for an international standardisation for different operators on social media, tablets, smartphones and wearables to enable a rule-setting force for all dominant players in the markets.

6. Conclusions

Big data is touted as an evolving research paradigm in numerous disciplines. However, only a handful of applications has investigated and ranked factors and their influence on firm performance in the field of hospitality. This study helps to increase the rate of BDA by clearly stating the innumerable advantages it offers. The uniqueness of this study lies in its application of an integrated analysis technique. First, we performed a comprehensive literature review, followed by expert interviews that revealed the possible factors. To prioritise the identified factors, we used an integrated AHP-DEMATEL technique on research data collected from managers and executives of Indian hospitality firms. We then used AHP to rank the identified adoption factors and DEMATEL to determine their interrelationships. The results demonstrated that technological factors – namely, big data quality and predictive analytics accuracy – exert a greater impact on the adoption of big data and firm performance than do organisational and environmental factors. This study represents an initial effort to utilise the AHP-DEMATEL method to examine BDA in hospitality firms using experts' opinions.

6.1. Limitations and future scope

The study has two major limitations: (a) although the authors finalised the factors very carefully, incorrectness may persist due to human bias, which relies on expert judgement, and (b) because the data were collected from three firms based in India, the generalisability of the study's results to other cultures and countries is limited. We recommend that scholars address these limitations in future studies. To this end, we suggest that (a) future studies complement the current study's findings by utilising other forms of data and research designs, e.g. experimental studies to establish causality and log-data to suggest associations, and that (b) scholars validate the current study's findings in other cultural and geographical settings. Furthermore, future research can compare findings in developing versus developed economies.

Note

1. Refer to Appendix for detailed methodology and step-by-step DEMATEL results for dimensions.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Qualitative Discussion Guide

Respondent's Profile

Name, Years of Experience, Title, Proficiency-Skills,
Years of Experience specifically in Big data analytics:

Information related to the Case organisation

Name, year when the organisation started, employees strength, annual gross revenue

Discussion Points

To clearly understand if the respondenthas knowledge and adequate cognizance of Big data analytics (BDA) in the domain of tourism/hospitality, the following points were discussed

(1) Had you ever heard of Big data analytics (BDA) and if so how do you relate BDA in tourism/hospitality and, also, could you explain what BDA can add to the functioning of BDA.
(2) If no then first explained our context of BDA and explained what we are trying to explore in tourism sector:
   (a) what is your understanding of large amount of data or Big data analytics with respect to tourism/hospitality.
   (b) What are the benefits for using data driven results
   (c) Does impact of data driven results on firm performance changes your idea to adopt Big data analytics with respect to tourism/hospitality?
   (d) For yes->
   (e) Has your organisation implemented any emerging technology such as cloud computing, big data or digital twin?
(3) Do you know data mining, natural language processing?
(4) Do you know machine learning?
(5) Do you think BDA can be/is costly?
(6) Please explain predicative modelling?
(7) The next few points revolve around their knowledge on data prediction and big data integration.
(8) Have you or do you plan to adopt Big data analytics with respect to tourism/hospitality. If yes, can you discuss why and how you adopted or plan to adopt the technology?
(9) How open are your stakeholders and other actors who play key role while taking adoption decision of any new technology and what was their reaction (BDA)?

(10) What are the parameters required for your firm to move towards new innovations/ideas or rechnology organisation?
(11) What motivated your organisation to use analytics?
(12) Please specify which things or factors motivate your firm to move towards BDA?
(13) Please specify which things or factors impede your firm while thinking about BDA implementation?
(14) Is there any functionality of process that you can achieve only with BDA that the existing system cannot provide?
(15) How your firm perceive advantages from BDA?
(16) Do you think your firm will need specific trainings or talent if you move towards BDA?
(17) Please specify if BDA has the capability to enhance business performance?
(18) Kindly explain if your firm expects any specific advantages from BDA-adoption.
(19) Please explain if your employees are open to innovation and their attitude to new innovations as well as BDA?
(20) Who are your competitors, are they adopting BDA driven results or promotions? If your firm is moving towards BDA owing to reasons like your competitors are thinking in same direction?
(21) How sure is your organisation that BDA will improve your overall-performance?
(22) Kindly explain the critical impediments for BDA in Indian hospitality context?
(23) What kind of response organisation has received from customers using BDA driven promotions?
(24) How important are organisational barriers such as senior management support for adoption of BDA or any other new technology?
(25) How important are environmental barriers such as competitive pressure or concerned actors/ stakeholders flexibility for BDA adoption?
(26) Do you feel size of organisation matters while making adoption decision for BDA?
(27) What are your thoughts on government policy for emerging technologies in Indian Do you think government policy are in place or do you feel more work needs to be done in right direction?
(28) What government initiatives are needed for faster propagation and acceptance of BDA.
(29) Since how many years the organisation is using Big data analytics with respect to tourism/ hospitality
(1) Technology implementation cost
(2) Cost savings with adoption of Big data analytics driven results

DEMATEL

For developing and examining a structural model, DEMATEL is utilised to uncover causal-effect relationships between determinats. The Battelle Memorial Institute first conducted DEMATEL at Geneva Research Centre to envision the structure and relations among identified determinants. DEMATEL utilises digraphs, or directed graphs, because they can determine the directed relationships among criteria. The following steps help to uncover the relationships and finally modelling into a logical structure.

(a) Using sacle of 0-4 (ranging from 'No' to 'Very' high influence), 1^{st} pairwise comparison among factors are done. This helps in providing pairwise direct relations matrix (DRM) between the criteria.
(b) The initial DRM Z is an $n \times n$ matrix where z_{ij} is the extent 'i' impacts the 'j'.
(c) To normalise the DRM A, i.e. $A = [a_{ij}]_{n \times n}$ where $0 \leq x \leq 1$, this regulates the initial influence matrix.
(d) The fourth step requires computing the total relation matrix T using the DRM (A) and the identity matrix (I).
(e) The final step involves calculating the rows sum (D) and columns sum (R).

Table A1. Expert data for categories influencing big data adoption and firm performance.

Factors	Environment	Organisation	Technology	Sum of rows
Environment	0	4	3	7
Organisation	3	0	2	5
Technology	1	1	0	2
			Max of sum	7

Table A2. Normalised value based on expert data for categories influencing big data adoption and firm performance.

Environment	0	0.571	0.428
Organisation	0.428	0	0.285
Technology	0.142	0.142	0

Table A3. DEMATEL results.

	Environment	Organisation	Technology	D	D + R	R – D
Environment	0.59	1.048	0.982	2.62	4.328	−0.912
Organisation	0.779	0.556	0.779	2.114	4.09	−0.138
Technology	0.339	0.372	0.252	0.963	2.976	1.05
R	1.708	1.976	2.013			