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Role of big data capabilities in enhancing competitive advantage and performance in the hospitality sector: Knowledge-based dynamic capabilities view

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ABSTRACT

To address the unsolved problem of the mechanism underlying the effect of big data analytics capabilities on competitive advantage and performance, this study combined quantitative and qualitative methods to test the examined framework. The results of 257 questionnaires from hotel marketing managers and 19 semistructured interviews, confirm that big data analytics capabilities develop from big data strategies and knowledge management and enhance competitive advantage and performance through sustainability marketing. Moreover, social media enhance sustainability marketing and competitive advantage and performance. The original findings of the current research contribute to the development of big data, sustainability marketing, and social media.

1. Introduction

The application of big data in today's technology can enhance the consumer experience and help consumers make purchasing decisions (Gavilan, Avello, & Martinez-Navarro, 2018). In the highly competitive hospitality industry, an increasing number of hoteliers have adopted big data to generate customer value (Hashem et al., 2015) and achieve differentiation through customized products (Samara, Magnisalis, & Peristeras, 2020). Big data allow companies to explore the unanticipated patterns of their customers, businesses and markets while also improving their understanding of customer behavior, which is one of the elements of competition in the hospitality sector (Talón-Ballestero, González-Serrano, Soguero-Ruiz, Muñoz-Romero, & Rojo-Álvarez, 2018). Members of the hospitality and tourism sector are active users of value creation through big data. For example, Xiang, Schwartz, Gerdes, and Uysal (2015) posited that big data assists hotels in understanding the factors contributing to customer satisfaction through big data text analysis of customer reviews on Expedia.com and similar websites. Shamim, Yang, Zia, and Shah (2021) that suggested practitioners in the hospitality sector can apply big data analysis in organizational business practice to facilitate service innovation.

When an organization begins to adopt big data, it can be regarded as implementing a new business plan. When promoting a new business plan, the organization must ensure that all members of the organization have a common vision, mission, goal, strategy implementation and evaluation from a strategic perspective (Witcher & Chau, 2014). By investigating how big data is involved in value creation, Shamim, et al. (2021) began from the strategic level to the operational level of big data management capabilities. Surprisingly, there is a lack of research in the existing literature that examines how big data can enhance competitive advantage from an organizational strategy perspective (Suoniemi, Meyer-Waarden, Munzel, Zablah, & Straub, 2020). Therefore, in response to Suoniemi et al. (2020), this study extends the previous model to examine the role of big data in organizations from a strategic perspective and proposes an integrated model from which to correctly understand the formation of competitive advantage by employing big data.

How to develop big data analytics capabilities is also an unveil issue. There are differences in the effectiveness of companies using big data to enhance their competitive advantage or corporate performance, and the

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key lies in its capability to analyze big data. Past studies have empirically demonstrated the relationship between big data analytics capabilities and performance (Ferraris, Mazzoleni, Devalle, & Couturier, 2019; Yasmin, Tatoglu, Kilic, Zaim, & Delen, 2020), but how to improve big data analytics capabilities needs to be further explored. Ali, Peters, Khan, Ali, and Saif (2020) pointed out that organizational learning is a kind of knowledge management and benefit to dynamic capabilities and improve organizational performance. Gupta and George (2016) believe that big data analytics capabilities can be improved from tangible assets, intangible assets, and human skills, but past research lacks empirical verification of big data knowledge management and big data analytics capabilities. From the KBDCs, this study believes that big data knowledge management is the key to improving big data analytics capabilities. In response to the research gaps, this research is based on KBDCs to explore the formation of big data analysis capabilities.

The knowledge-based dynamic capabilities (KBDCs) view proposed by Mikalef, Pappas, Krogstie, and Giannakos (2018) and Zheng, Zhang, and Du (2011) provides a solid theoretical foundation for addressing the above issues and contributes to the development of the framework. The KBDCs theory combines dynamic capabilities with a knowledge-based perspective. Dynamic capability can exist at all levels in organizations, such as among individuals, organizations, strategies and operational levels (Teece, 2007; Teece, Pisano, & Shuen, 1997), while the knowledge-based view regards knowledge as a critical asset that can generate a competitive advantage for a company (Grant, 1996; Shamim, Cang, & Yu, 2019). Consistent with KBDCs, we believe that big data analytics capabilities are critical to creating value from big data. However, organizations not only require access to big data but also must create value from a strategic perspective. Shamim, Zeng, Shafi Choksy, and Shariq (2020) posited that dynamic capabilities developed from big data are actually KBDCs because big data lead to the formation of new knowledge, which in turn enables dynamic capabilities such as innovation. Shamim et al. (2021) also indicated that big data management capabilities at the strategic and operational levels are positively related to knowledge creation and service innovation. In addition, hotel managers can achieve many positive outcomes by enhancing knowledge management, such as innovative service behavior, financial performance, and competitiveness (Shamim, Cang, & Yu, 2017).

Big data can be collected from social media or review sites such as Facebook, Twitter and LinkedIn (Chua, Servillo, Marcheggiani, & Moere, 2016) and TripAdvisor and Yelp (Viglia, Minazzi, & Buhalis, 2016). All hospitality companies can collect these data, but companies vary in their ability to manage big data (Li, Kim, & Choi, 2021). With the growing importance of social media in terms of generating website traffic and increasing business awareness (Anderson, 2012; Murdough, 2009), scholars in different fields have tried to explore the effectiveness of social media marketing. To increase popularity and profitability, an increasing number of hospitality firms are combining social media with promotions to increase social sharing and potential customer engagement (Li et al., 2021). By monitoring social media, hotels are able to forecast consumer preferences via data available from social media, which they can then use to optimize demand (Xiang et al., 2015). This study incorporates two moderating variables, proactive social media orientation and social media customer collaboration. The former involves the discovery of unknown consumer needs; the latter involves the interaction between consumers and participating companies to create value. This study argues that these two types of social media strategies can substantially enhance the competitive advantage and intangible assets of companies.

To address these critical unsolved issues, we propose a new model for starred hotels, and our objectives are as follows. (1) This study strives to answer the key question of whether a big data strategy enhances competitive advantage and company performance by adopting sustainability marketing for starred hotels. If so, how do big data play a role in the formulation of competitive advantage and company performance? (2) We examine the mediating role of big data knowledge management and sustainability marketing and clarify ways to form big data analytics capabilities within organizational internal mechanisms. In addition, we explore ways to enhance competitiveness through sustainable marketing when an organization has big data analytics capabilities. (3) Finally, we explore the role of social media in the process of sustainability marketing and in further enhancing competitive advantage and company performance.

The newly integrated framework proposed in Fig. 1 not only fills gaps in research on hotel big data analytics capabilities in terms of big data strategies, big data knowledge management and sustainability marketing but also provides a new perspective on ways to rebuild competitive advantage and company performance in the hotel industry based on KBDCs, sustainability marketing, knowledge management, and social media marketing.

2. Literature review and research hypothesis

2.1. Knowledge-based dynamic capability view

Dynamic capability (DC) theory is an extension of resource-based theory. The resource-based view (RBV) emphasizes that an organization can gain a sustainable competitive advantage if it has heterogeneous strategic resources. Critics of the RBV argue that the RBV view resources are limited (Felin & Hesterly, 2007) and ignore the external environment related to the business (Cepeda & Vera, 2007). Thus, researchers extend the RBV to DC (Gutierrez-Gutierrez, Barrales-Molina, & Kaynak, 2018; Hitt, Xu, & Carnes, 2016; Teece et al., 1997). DC refers to a firm's ability to sense and seize opportunities in the external environment, create new capabilities, and reconfigure existing capabilities according to changes occurring in the external environment (Teece et al., 1997; Teece, 2007). This perspective asserts that strategic resources alone without effective management practices are not sufficient to ensure a sustainable competitive advantage (Teece, 2007; Zheng et al., 2011). Combined with other theories, the DC view can be used to explain the competitive advantage of each industry (Wamba et al., 2017). Considering that the focus of this study is the importance of big data analytics capabilities, we combine DC with the knowledge-based view (KBV) to support our theoretical model. The KBV views knowledge as a key strategic resource that can help organizations gain a competitive advantage (Grant, 1996; Shamim, Cang, & Yu, 2019) and views organizations as knowledge-bearing units with the aim of using knowledge to create business value (Donate & Sanchez, de Pablo 2015; Grant, 1996).

In combining the KBV and DC, KBDCs is defined as the capability to acquire, create, and assemble knowledge to sense, explore, and resolve environmental dynamics (Mikalef et al., 2018; Zheng et al., 2011). KBDCs is premised on the notion that managers can create new value by integrating existing knowledge (Zheng et al., 2011). Organizations with dynamic capabilities are agile and can operate in a dynamic and stable business environment. Knowledge acquisition, knowledge generation and integration capabilities are subfunctions that represent the dimensions of KBDC (Zheng et al., 2011). This study discusses the strategic dimension and proposes that big data strategies can enhance capabilities through big data knowledge management and contribute to competitive advantage and performance.

Big data has been applied in many aspects of business practices such as decision making (Awan et al., 2021; Nisar et al., 2021; Shamim, Zeng, Shariq, & Khan, 2019), marketing (Shamim et al., 2021) and production (Hazen, Skipper, Boone, & Hill, 2018). Big data analytics capabilities play a crucial role in ensuring the integration of big data into business processes (Kim, Shin, Kim, & Lee, 2011). We consider big data analytics capabilities to be a form of KBDCs because they relies heavily on knowledge and have a positive impact on quality in a given context. Big data management capabilities enables companies to process and analyze big data to create knowledge (Shamim et al., 2021). The literature supports the argument that knowledge creation comes from data

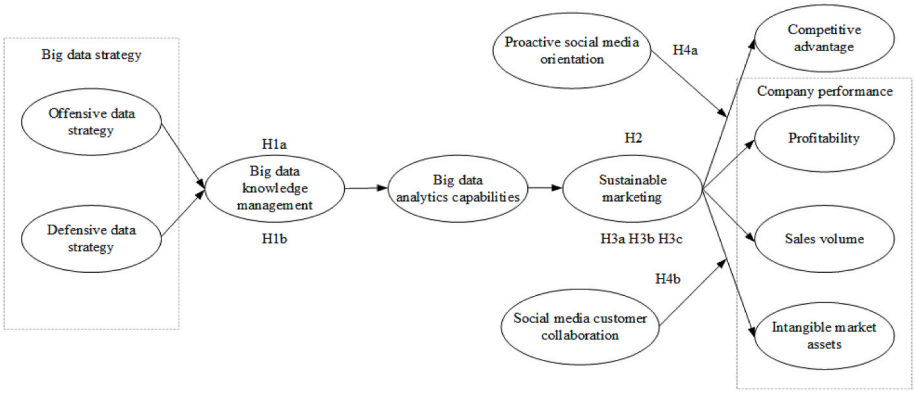

Fig. 1. Proposed research framework.

analysis and understanding data patterns (Uriarte, 2008; Shamim et al., 2021). Existing research has also used the KBDCs framework to demonstrate the relationship between knowledge and capabilities at the strategic level (Zia, 2020; Shamim et al., 2021).

2.2. Big data strategy, big data knowledge management and big data analytics capabilities

Big data refers to data with features such as large volume, velocity, variety, and value (Ghasemaghaei & Calic, 2020). Big data enable companies to make decisions on the basis of evidence rather than relying solely on intuition (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). In the hospitality sector, big data can be generated by devices and operations (Li, Xu, Tang, Wang, & Li, 2018), and customers can be generated using hospitality firm platforms (Xiang et al., 2015), customer reviews (Xiang et al., 2015), and social media platforms (Chua et al., 2016). Through big data analytics capabilities, big data can be analyzed and customized according to the specific requirements of a given organization. This approach helps in understanding performance standards, evaluating the environment, analyzing trends and predicting future results and developing optimal strategies (Delen & Zolbanin, 2018), allowing organizations to better understand their customers and direct process optimization to improve efficiency and effectiveness (Wamba et al., 2017), thereby leading to increased productivity and organizational performance (Müller, Fay, & vom Brocke, 2018).

Mazzei and Noble (2017) state that using data as part of a strategy implies that organizations are committed to constructing data resources that enable them to develop radically innovative business models. The authors define a big data strategy as an organization's long-term decision on how to use its data performance actions to achieve its mission and organizational value. A big data strategy involves instructing an organization on how it should use big data analytics capabilities to help differentiate itself from competitors and achieve a competitive advantage; identifying an organization's long-term analytics guidelines; demonstrating how an organization can select analytics opportunities that optimize value; indicating how value generated from selected analytics opportunities should be quantified and tracked; and informing an organization how it should manage data as a corporate asset (Grossman, 2018). Mazzei and Noble (2017) state that there are two types of big data strategies: defensive and offensive. Defensive positioning is a passive position taken in response to competitive forces in the industry, so the role of the strategy is to establish a defensive or protected position against such forces (Porter, 1991; Spanos & Lioukas, 2001). According to DalleMule and Davenport (2017), most defensive data strategies (DDSs) can be defined by the following objectives:

- reduce operating expenses and streamline business processes;
- meet industry sectors' regulatory requirements;
- prevent cyber-attacks and data breaches;
- mitigate operational risks such as poor access controls and data loss;
- improve information and technology infrastructure and reduce data costs
- develop analytical and digital capabilities;
- improve data quality (integrity, precision and accuracy); and
- rationalize multiple sources of data and information (consolidate and eliminate redundancy).

Offensive positioning adopts a more aggressive and proactive stance, indicating that an organization is focused on exerting its market power and altering the balance in its favor (Porter, 1991; Spanos & Lioukas, 2001). According to DalleMule and Davenport (2017), most offensive data strategies (ODSs) can be defined by the following objectives:

- improve revenue through cross selling, strategic pricing and customer base expansion;
- create new products and services;
- respond quickly to competitors and market changes;
- use sophisticated customer analysis to generate business results;
- leverage new data sources, internal or external;
- monetize company data;
- optimize and strengthen the existing database of data scientists
- generate return on investment in big data analytics' infrastructure.

Big data analytics capabilities refer to obtaining knowledge from internal or external partners and gaining market insight through big data tools (Germann, Lilien, & Rangaswamy, 2013). Indeed, big data analytics capabilities gaps are considered to be a major barrier to the adoption of big data-driven marketing strategies (Brown, Chui, & Manyika, 2011). In short, companies require data scientists who can find patterns in large amounts of multistructured data and translate them into useful and actionable insights (Davenport & Patil, 2012; Hopkins, 2011; McAfee, Brynjolfsson, 2012). Since most of the data generated today are in the form of unstructured text and increasingly in the form of video, audio and graphics, the available data have become less straightforward than structured and organized data. Individually, most of the isolated messages generated by consumers provide little inspiration to marketers. However, when aggregated, they can reveal patterns and provide insights that can serve as important information for researchers and managers.

Organizations must be able to effectively implement big data analytics capabilities to extract valuable information and must rely on and obtain key resources (Mikalef, Framnes, Danielsen, Krogstie, & Olsen, 2017). Tangible resources, intangible resources, and human skills are three distinguishing resources proposed by Gupta and George (2016) to develop big data analytics capabilities. Tangible resources are represented by internal and external data integration technologies, data storage, processing, analysis and visualization technologies and investments dedicated to big data initiatives (Gupta & George, 2016).

Intangible resources include data-driven and evidence-based decision--making, a corporate culture oriented to any level of the organization (Ross, Beath, & Quaadgras, 2013), and the intensity of organizational learning, which involves the acquisition, sharing, interpretation, storage and application of knowledge extracted from big data by an organization (Pérez López, Manuel Montes Peón, & JoséVázquez Ordás, 2004). Finally, human skills represent the technical, managerial, and relational skills possessed by professionals (e.g., data analysts and data scientists) and other employees who are essential to the effective implementation of big data analytics capabilities. (Wamba et al., 2017). The development of adequate big data analytics capabilities allows organizations to effectively leverage insights extracted from large datasets by using them to make business decisions through the use of advanced knowledge management systems.

Previous studies have shown that knowledge generation and dissemination are unique to firms and therefore play a critical role in gaining a sustainable competitive advantage (e.g., innovation) (Day, 1994; Grant, 1996). According to Meso and Smith (2000), knowledge management (KM) is "the process of acquiring collective expertise and wisdom in an organization and using it to promote innovation through continuous organizational learning" (p. 225). KM captures the changes that occur in the environment and supports companies in integrating, structuring, and reconfiguring their capabilities. From this perspective, KM has been related to corporate practices such as organizing knowledge repositories, adopting technologies that allow data collection from internal and external sources, and developing mechanisms for sharing and transferring knowledge (Darroch & McNaughton, 2002; Gupta, Iyer, & Aronson, 2000). According to KBDCs, knowledge management can be categorized into knowledge acquisition, knowledge generation, and knowledge combination (Zheng et al., 2011). Knowledge acquisition means that an organization is able to recognize the value of new, external information, assimilate it, and apply it to commercial ends (Cohen & Levinthal, 1990, p. 128). Knowledge generation is defined as the extent to which an organization is able to develop and modify processes that contribute to creating new knowledge (Zheng et al., 2011). Knowledge generation requires knowledge workers to interact within organizations. In this way, they can create new knowledge. Knowledge combination refers to the organization's ability to coordinate and apply knowledge gained from internal and external resources (Zheng et al., 2011).

From the KBDCs perspective, big data at the strategy level provides guidance to the organization and its members and aligns the overall content through mission, vision, goals, strategy implementation and evaluation. (Witcher & Chau, 2014). Big data knowledge management regards big data related to knowledge as an asset and enhances the capabilities of organization members through the process of KM such as data experts and nondata experts collaborating across departments (Shamim et al., 2021). Knowledge management can be regarded as a mode of organizational learning (Andrews & Delahaye, 2000; Nonaka, 1994). This conceptualization of knowledge management has been used in research in the hospitality and tourism industry (e.g., Lemmetyinen & Go, 2009; Thomas & Wood, 2015). In this vein, some scholars explored the development of organization dynamic capabilities by knowledge management view. For example, Zollo and Winter (2002) viewed learning and knowledge management as a facilitator of dynamic capabilities' development. Nieves and Haller (2014) and Leonidou, Leonidou, Fotiadis, and Aykol (2015) revealed that the view of knowledge based on an organizational learning approach can enhance hotels' dynamic capabilities. Ali (2020) also found strong direct inter-relation between organizational learning, dynamic capabilities, and performance in the hotel industry of United Kingdom and Pakistan. Moreover, previous empirical studies have shown that to enhance knowledge creation, firms have to start from the strategic level (Shamim et al., 2021). Shamim, Zeng, Khan, and Zia (2020) argued that dynamic capabilities such as big data analytics capabilities can be influenced by knowledge sources and activities. This finding also contributes toward the KBDCs view of firms. Khaksar, Chu, Rozario, and Slade (2020, pp. 1–18) suggested that KDBCs can enhance knowledge worker productivity which comprises knowledge acquisition, knowledge generation, and knowledge combination. Vidgen, Shaw, and Grant (2017) also note that using data as a driver is not simply a technical issue but requires organizations to align their business analytics functions with their business strategies. Therefore, it is rational to argue that organizations want to improve their employees' big data analysis capabilities, and they have to start from the strategic level. From the perspective of KBDCs, since knowledge is a strategic asset, the promotion of big data knowledge management within the organization can promote knowledge exchange and enhance employees' big data analytics capabilities. Based on this discussion, we propose the following:

Hypothesis 1a. Big data knowledge management mediates the relationship between offensive data strategy and big data analytics capabilities.

Hypothesis 1b. Big data knowledge management mediates the relationship between defensive data strategies and big data analytics capabilities.

2.3. Sustainable marketing

Sustainable marketing is "a management process responsible for identifying, anticipating and satisfying customer and social needs in a profitable and sustainable manner" (Finisterra do Paço, Barata Raposo, & Filho, 2009, p. 18).

KBDC can link resources, knowledge, capabilities and competitive advantages, and is an influential theory in marketing research (Kozlenkova, Samaha, & Palmatier, 2014; Srivastava, Fahey, & Christensen, 2001). In this vein, Day (1994) and Vorhies and Morgan (2005) treat big data analytics capabilities as a strategic firm capability. We argue that an organization can use big data analytics capabilities to understand and meet customer needs and provide products or services (Day, 1994; Krasnikov & Jayachandran, 2008). Finally, sustainable marketing enhances marketing performance and results in a the competitive advantage.

Previous studies provide substantial support for this theory, as it has been found that business capabilities can mediate the impact of IT on firm performance (Chae, Koh, & Park, 2018; Ngo & O'Cass, 2012). Most of these studies involve process-related mediators such as innovation capabilities, while mediators related to big data, customer relationship management (CRM), social media technologies, and firm performance have received less attention (Foltean, Trif, & Tuleu, 2019). IT business value studies have shown that the impact of IT resources and capabilities on firm performance is indirect and achieved by complementing non-IT resources and capabilities (Bharadwaj, 2000; Ravichandran, Lertwongsatien, & Lertwongsatien, 2005).

Hypothesis 2. Sustainability marketing mediates the relationship between big data analytics capabilities and competitive advantage.

Hypothesis 3a. Sustainability marketing mediates the relationship between big data analytics capabilities and profitability.

Hypothesis 3b. Sustainability marketing mediates the relationship between big data analytics capabilities and sales volume.

Hypothesis 3c. Sustainability marketing mediates the relationship between big data analytics capabilities and intangible market assets.

2.4. Social media

Social media marketing is the process of gaining traffic from social networks (Evans, 2010). Social media marketing allows advertising and marketing related practitioners to find potential customers and explore business opportunities (Kumar & Mirchandani, 2012). For example, the feature of social media that connects individuals with each other allows

everyone to create and distribute advertisements and ultimately influence future behavioral intentions. (Lee and Cranage, 2014). Past marketing literature has noted that organizations use social media to promote brands online, maintain dialog with active customers, respond to customer reviews, increase website traffic, advertise products, generate new business opportunities, and create communities (Breslauer & Smith, 2009; Kumar & Mirchandani, 2012; Xie & So, 2018).

Proactive market-oriented firms identify and understand the potential needs of their customers. These potential market needs in turn lead to the generation of new technological capabilities from internal and external sources (e.g., primary users or customer needs) (Deshpande, Farley, & Webster, 1993; Hurley & Hult, 1998).

Researchers believe that proactive market orientation and meeting potential customer needs can lead to more innovative ideas, products, and services (Narver, Slater, & MacLachlan, 2004). Atuahene-Gima, Slater, and Olson (2005) state that proactive market orientation involves an "outside-in" process that focuses on identifying customer needs. Thus, proactive market orientation uses customer knowledge to develop new ideas on social media (Levinthal & March 1993).

Customer collaboration through social media refers to the information received from customers to actively interact and collaborate with a company through the value cocreation process (Constantinides, Romero, & Boria, 2009). For value cocreation, customers are fundamental participants and active coinventors of value (Lusch, Vargo, & O'Brien, 2007; Vargo & Lusch, 2008; Vega-Vazquez, Ángeles Revilla-Camacho, & J. Cossío-Silva, 2013), and social media; interactions between customers and firms and among peers and the sharing of information, benefits and perspectives facilitate the value cocreation process (Harrison & Barthel, 2009). Social media allows companies to create value directly and continuously with customers and to develop learning processes (Sawhney, Verona, & Prandelli, 2005). Thus, by using social media, companies can build relationships with existing customers, acquire new customers and build interactive and collaborative communities to identify and understand existing and potential needs and develop solutions (Sashi, 2012). Collaborating with customers through social media is a major barrier to companies acquiring customer-related data, which in turn needs to be managed appropriately to gain customer knowledge useful for supporting the cocreation process (Bharati, Zhang, & Chaudhury, 2014; Fidel, Cervera, & Schlesinger, 2016). From a dynamic capability perspective, working with customers allows companies to gain the external knowledge needed to generate new learning and to accumulate experience that can help to develop a lasting competitive advantage (Alegre, Sengupta, & Lapiedra, 2013; Marsh & Stock, 2006). In the hospitality industry, consumers are increasingly aware of the need for sustainability and responsible consumption (Njite & Schaffer, 2017). However, consumers may not choose sustainable hotels. Research suggests that green hotel practices are not as important as other hotel attributes (Njite & Schaffer, 2017), and many customers are reluctant to pay more. Tanford, Kim, and Kim (2020) note that by using social media marketing, hotel operators can not only induce emotional activation in consumers but also improve hotel image and subsequent booking intentions as consumers engage in the online purchase process. Hotels can immediately improve their image by using pleasant music, videos or photos on booking sites to manipulate consumer emotions. Through social media, service providers in the tourism industry can increase environmental awareness and attitudes based on consumers' voices. Social campaigns are not directly related to immediate sales and can improve business performance by improving brand image and awareness of social issues (Tanford et al., 2020).

Hypothesis 4a. Proactive social media orientation moderates the relationship between sustainable marketing and competitive advantage.

Hypothesis 4b. Social media customer collaboration moderates the relationship between sustainable marketing and intangible market assets.

3. Methodology

3.1. Research design

We adopted a mixed method since many tourism and hospitality scholars have recently used mixed methods for the following reasons (Pham, Tučková, & Chiappetta Jabbour, 2019; Zhang, Li, Liu, & Ruan, 2021). First, the mixed-method approach uses more than one qualitative or quantitative method, to combine the advantages of the two methods to increase the generality of the results and prevent deviation of the research method. Second, the mixed-method approach provides better research results (Tashakkori & Creswell, 2007). We use qualitative cross-validation to quantify the results of the study, to improve the study's reliability and validity (Zhang et al., 2021). Finally, the mixed method approach is suitable for studying complex research topics. The proposed research framework is more complex than that of past research. Therefore, according to Pham et al.'s (2019) recommendations, we collected data through quantitative research and validated our Hypothesis. Finally, semistructured interviews were used to verify the quantitative results.

3.2. Methods for study 1 quantitative approach

We employed a quantitative method to verify the theoretical model. We collected data for statistical analysis using the survey method. We selected directors of marketing of hotels with 4 stars or above as our participants for the following reasons. First, we focus on the big data approach to marketing issues and on exploring whether the adopted marketing strategy can improve hotel performance. Second, directors of marketing are decision makers who coordinate marketing strategies and realize the stages of marketing plans from creative idea development to actual output. In addition, Taiwan's hotel industry has experienced 10 years of steady growth. Its scale grew from NT$43 billion in 2010 to nearly NT$60 billion in 2019. The number of tourists served each year has also grown from 9.71 million to 13 million. Before COVID-19, 11.86 million tourists came to Taiwan in 2019, a record high. At present, more than 13,000 hotel operators are registered officially (Taiwan Tourism Bureau, 2020). Even during the COVID-19 epidemic, international hotel chains are still actively entering the Taiwanese market; for example, Kaohsiung Marriott Hotel, Tapestry Collection by Hilton, Holiday Inn Express Chiayi at the end of 2020; in 2021, there will be InterContinental Kaohsiung, Hotel Metropolitan Premier Taipei, and Hotel Gracery Shinjuku. Therefore, Taiwan's hotel industry is an emerging market in the Asia-Pacific region. Finally, hotels in Taiwan with clearly defined functions in marketing divisions are still dominated by international chain brands or medium- or large-scale brands (Huang, Ho, & Chen, 2015), mainly because their business scope is more complex and enables an investment of more resources. Therefore, we believe that marketing executives of hotels with 4 stars or above are representative.

3.2.1. Sample and data collection

Surveying the directors of hotel marketing departments proved to be more complicated than surveying consumers. To improve the efficiency of questionnaire distribution and sample quality, we commissioned a polling market research consultancy to distribute the surveys. The POLLS Market Research Consultancy consists of experts with specialization in domestic and foreign market research, statistics and marketing. POLLS integrates 30 years of experience in delivering market surveys. As of January 2019, POLLS had completed 3368 projects with 2368 companies worldwide. POLLS possesses a database of millions of samples in Taiwan, which is the epitome of the Taiwanese market. The survey process involved the following: (1) The researcher informed the polling market research consultancy of the criteria for the samples, and questionnaire distribution began when the evaluation was confirmed to be practical. (2) The polling market research consultancy screened eligible participants from the database, and well-trained assistants asked the

eligible individuals to participate by telephone and emphasized that the questionnaire should only be answered based on their actual feelings and that there were no right or wrong answers. Anonymity was also ensured. (3) When participants agreed to participate in the survey, the online questionnaire was sent to them via email so that they could complete the items online. (4) After completing the questionnaire, the assistants checked the answers and eliminated invalid questionnaires. Before the formal survey, 30 directors of marketing working in the international tourist hotel industry were pretested to correct any misunderstanding of the questionnaire's items and to examine its validity and reliability. After checking all of the above criteria, the questionnaire was then revised according to the suggestions and opinions of the participants to reach better scale consistency. The formal survey was conducted from November 2020 to January 2021. A total of 560 questionnaires were distributed, and 257 valid responses were obtained, for a response rate of 45.89%. Descriptive statistics for the participants are summarized in Table 1.

To ensure content validity, all items used in this study are derived from past research. Researchers and other bilingual scholars translated the items into Chinese. Further back translation was conducted to ensure that the Chinese version of the items was consistent with the original scale (Liu, 2018).

3.2.2. Measurements

To verify the hypotheses of this study, eight variables were measured using reliable and valid scales cited in relevant past studies. All items used a 7-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7). First, we adopted fifteen items to measure big data strategies following DalleMule and Davenport (2017), reflecting an organization's attitude regarding promoting big data on a strategic level. The items cover 2 dimensions: 7 items for offensive data strategy and 8 items for defensive data strategy. Medeiros, Maçada, and Freitas Junior (2020) also adopted this scales and used in Brazilian companies. Second, to measure big data knowledge management, we used Alegre et al.'s (2013) and Fidel et al.'s (2016) 7 items to represent the application of knowledge management in big data strategies. In Fidel et al. (2016)'s study, a total of 72.33% of the samples come from the service industry. Third, bid data analytics capabilities were measured using three items developed by Kamble and Gunasekaran (2020) reflecting the capabilities of big data in organizations. Fourth, following Chou, Horng, Sam Liu, and Lin (2020), we proposed 11 items to measure sustainability marketing that reflect organizational commitment to sustainability in marketing activities. The scale of sustainable marketing was originally used in restaurant settings (Chou et al., 2020) and later extended to tourism and hotels (Liu & Dong, 2021). Fifth, we used 6 items from Saeidi et al. (2019) to measure competitive advantage, representing the impact of big data strategies on organizational competitiveness. Sixth, a 9-item scale developed by Moorman and Rust (1999) and Vorhies and Morgan (2005) was used to measure company performance, including the three subdimensions of profitability (3 items), sales volume (3 items), and intangible market assets (3 items). The measurement of performance is mainly divided into objective measurement and subjective measurement, that is, the use of managerial perceptions. Due to sample size, unwillingness to share actual performance data, and we focus on the difference in performance compared with other hotels that have not adopted big data. This study followed most strategy research and opted to collect managers' subjective perceptions of performance (Moorman & Rust, 1999). Previous studies have found a strong correlation between subjective assessments and their objective counterparts (Dess & Robinson, 1984). This approach has been taken in hospitality and tourism literature (Hameed, Nisar, & Wu, 2021; Pertusa-Ortega, Tarí, Pereira-Moliner, Molina-Azorín, & López-Gamero, 2021) and found to compare well to evaluations of firm performance relative to competitors (Moorman, 1995). Seventh, variables for social media customer collaboration (4 items) were drawn from Fidel et al. (2016) to indicate that consumers had collaborated with a company through social media. Finally, 4 items adopted from Nguyen, Yu, Melewar, and Chen (2015) were used to measure proactive social media market orientation. Proactive social media market orientation and social media customer collaboration was used in Chierici, Mazzucchelli, Garcia-Perez, and Vrontis (2019). The respondents for the questionnaire were managers of marketing, advertising and communication in the Italian market.

Table 1
Descriptive statistics.

Items	Frequency	Percent
Gender		
Male	125	48.60%
Female	132	51.40%
Age		
20–29	10	2.80%
30–39	150	58.40%
40–49	92	35.80%
50–59	3	1.20%
Above 59	2	0.80%
Education		
Senior high school	32	12.40%
University	144	56%
Graduate school	74	28.80%
Ph.D	7	2.70%
Position		
Director of marketing	207	80.50%
CEO	39	15.20%
Founder	10	3.90%
Other	1	0.40%
Tenure		
Under 5	12	4.70%
5–9	91	35.40%
10–14	59	23%
15–19	79	32.70%
20–24	12	4.60%
Above 25	4	1.60%
Tenure in hotel		
Under 5	82	31.90%
5–9	108	42%
10–14	57	22.20%
15–19	9	3.60%
Above 20	1	0.40%

3.3. Methods for study 2: qualitative approach

To prevent the results from being distorted by common method variance (CMV), we follow Podsakoff's (2003) suggestion to eliminate CMV in the research design. In procedural controls, the researchers emphasized that the survey results would be kept anonymous, that there were no correct or incorrect answers, and that the respondents could answer based on their actual feelings. We also designed inverse items to test whether the respondents were attentive to their answers and nondisclosure of the purpose of the research. In statistical controls, Harman's (1976) one-factor test showed that 44.02% of the variance was explained by the first factor at less than 50%. In addition, the unmeasured latent method construct (ULMC) approach (Liang, Saraf, Hu, & Xue, 2007) is used to test whether there is a single index variable with a common method factor that includes all of the main variables. When the source of common method bias is not known prior to data collection, Kock, Berbekova, and George Assaf (2021) suggest that researchers employ marker techniques or the technique of unmeasured latent method constructs. The ULMC method is also popular in hospitality research. Min, Park, and Kim (2016) examined the effectiveness of this technique in assessing the relationship between service quality and behavioral intention in a hospitality context. The authors concluded that the unmeasured latent method construct technique is an adequate method to control for common method bias. Suess, Woosnam, and Erul (2020) also assessed the threat of common method bias using the unmeasured latent construct through CFA. As the results showed, CMB was not a concern for the study. The results of the ULMC analysis show that

the majority of the common method factor path coefficients are not significant, the average substantively explained variation of each index is .67, the average variation of the common method is 0.016, and the ratio of the two is 42:1. According to the above detection procedures, this study was not seriously affected by CMV.

3.3.1. Sampling procedure

We adopted qualitative research using mixed research methods to further verify the framework. Specifically, the qualitative findings show the mechanism of the hotel industry between big data, knowledge management, sustainable marketing, and social media marketing, which provides a deeper understanding of our theoretical framework and its role in the hotel industry.

3.3.2. Data collection

The qualitative data collection stage, following the recommendations of Pham et al. (2019) and Ghaderi and Béal (2020), was divided into the following steps. First, the purpose of the interviews was to verify the results of the statistical analysis. We adopted semistructured interviews and developed interview guidelines to allow the interviewers to follow a standardized process. Before the interviews, the interviewers received training on information acquisition, ethical and moral issues, and interview skills. There are three types of experts invited for in-depth interviews in this study. First, we invited marketing executives from 4-star and 5-star hotels across Taiwan via e-mail. Before the interviews, the interviewers explained the purpose of the research by e-mail and attached an interview outline to inquire about each interviewee's willingness to participate in an interview. A total of 7 interviewees were included. Second, scholars in the hotel industry and big data recommended suitable interviewees, and then the researcher personally invited them to participate in this research. A total of 6 interviewees accepted the invitation. Finally, at the end of each interview, the researcher asked the interviewees to recommend suitable candidates for interviews in the hotel industry. A total of 6 interviewees accepted the invitation. If a respondent was willing to be interviewed, face-to-face interviews were arranged according to the respondent's schedule. Audio-recording was performed throughout the interviews with the consent of the interviewees. Most of the interviews were held in meeting rooms at the interviewees' firms, as this was more convenient for the interviewees and provided a quiet environment conducive to recording. Before a formal interview, the interviewer again explained the purpose of the research and emphasized the participant's anonymity and that the results would not be analyzed with reference to a single company. Finally, 16 marketing directors and 3 general managers were interviewed, one of whom refused to be audio recorded. In total, 18 audio-recorded files were obtained. For interviews that were not recorded, an assistant took notes by hand.

For the interviews, we followed Chan and Hawkins's (2012) three-stage interview approach, which includes warm-up, development, and closing stages. In the warm-up stage, the interviewer explained the purpose of the research, emphasized the participant's anonymity and confirmed that the results would not be analyzed in reference to a single company. We asked the respondents to answer according to their real feelings. During the development stage, the interviewer asked open-ended questions about big data marketing in the hotel industry according to the interview outline. When other issues were raised, the respondent was immediately asked to elaborate.

Each interview lasted approximately 1 h. After the 19th interview, we identified no new insights, which means that the interviews reached saturation. Finally, the audio recordings were transcribed. To reduce deviation, we had the interviewees revise the transcriptions if necessary (Molina-Azorín, Tarí, Pereira-Moliner, López-Gamero, & Pertusa-Ortega, 2015).

4. Results

4.1. Quantitative results: study 1

We performed structural equation modeling (SEM) with AMOS 24.0 software to examine the hypotheses. Following Anderson and Gerbing's (1998) two-stage approach, confirmatory factor analysis (CFA) was conducted to verify the measurement model. When a good model fit was achieved, a structural model was used to test the hypotheses. AMOS software provides a bootstrap confidence interval approach and Monte Carlo analysis with 20,000 resamplings (So, King, Sparks, & Wang, 2013), making the results more robust. For our moderation analysis, we conducted a hierarchical regression using SPSS 24.0 software and a parsimonious latent-variable interaction technique (e.g., Ping, 1995) via AMOS 24.0. This dual testing allows for a robust assessment of the hypotheses within the different strengths and constraints of each technique (e.g., Shook, Ketchen, Hult, & Kacmar, 2004). The moderation effects of latent variables are commonly examined using hierarchical regression analysis with cross terms generated on the summed indicants of independent variables (Ro, 2012) or multigroup structural equation modeling (SEM), which creates subgroups using the summed scores of moderators and then tests for significant coefficient differences among the groups (Myers, Calantone, Page, & Taylor, 2000). Product term regression lacks statistical power for latent variables measured with errors (Aiken, West, & Reno, 1991), and although hierarchical regression analysis has weaknesses, the strengths of hierarchical regression allow the direct assessment of change in explanatory power between iterative steps and provide a baseline set of results for our predictions. Multiple-group SEM can cause a loss of information and a reduction in power for detecting interaction effects (type II error) by artificial grouping (Frazier, Tix, & Barron, 2004). Therefore. We used a single-indicant latent-variable interaction technique developed by Ping (1995). This is because the single-indicant latent-variable interaction technique has several merits. This technique is a more parsimonious estimation technique for latent interaction and quadratic variables than its predecessors by Kenny and Judd (1984) and Hayduk (1987). This technique was used to examine the hypotheses by adding hierarchical regression analysis in two ways. First, the single-indicant latent-variable technique allows us to incorporate measurement errors for the main and interaction effects (Ping, 1995) to assess whether such errors undermine any statistically significant links within the results (Busemeyer & Jones, 1983). Ping (1995) proposes a simplified moderated structural equation modeling approach with only one indicant for each interaction term, which can avoid redundant variables that are problematic with convergence and infeasible solutions in larger models (Cortina, Chen, & Dunlap, 2001). Second, we are able to incorporate a test of potential CMV issues at the Hypothesis-testing level to determine whether CMV inflates or curtails the magnitude of the obtained effects (e.g., Netemeyer, Boles, McKee, & McMurrian, 1997; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). This single-indicant latent-variable interaction approach has been used by a number of hospitality studies (Han & Hwang, 2019; Lei, Ye, Wang, & Law, 2020; Ye, Wu, & Zheng, 2019).

4.1.1. Reliability and validity

Before verifying the hypotheses, a preliminary analysis of reliability and validity was conducted. Table 2 reveals a CR value greater than 0.80, and AVEs greater than 0.50, showing a high level of reliability (Anderson & Gerbing, 1988). Furthermore, a CFA with the robust maximum likelihood method was conducted to test for validity. The results fit the data well in the first-order model ($\chi2 = 197.996$, $p < .001$; $\chi2/df = 2.357$, CFI = 0.986, NNFI = 0.977, RMSEA = 0.052). In the second-order model, the data strategy model with the two dimensions of offensive and defensive data strategies indicates a good model fit ($\chi2 = 48.902$, $p < .001$, $\chi2/df = 2.126$, CFI = 0.995, NNFI = 0.991, RMSEA = 0.047). Moreover, the company performance model, including the three dimensions of profitability, sales volume, and intangible market assets,

Table 2
Results of confirmatory factor analysis.

Constructs and items	Mean	S.D	Factor loading	CR	AVE
Offensive data strategy				.87	.52
Data strategy improves revenue through cross-selling, strategic pricing and expanding customer base	5.51	.97	.77		
Data strategy helps to create new products and services	5.65	.97	.76		
Data strategy encourages the use of sophisticated customer analytics to generate business results	5.51	.98	.76		
Data strategy leverages new data sources, internal or external	5.56	.92	.70		
Data strategy helps monetize business data	5.63	.87	.67		
Data strategy improves return on investments in BDA infrastructure	5.53	1.04	.66		
Defensive data strategy				.89	.54
Data strategy helps meet industry regulatory requirements	5.31	1.03	.66		
Data strategy helps prevent cyber-attacks and data breaches	5.22	1.10	.69		
Data strategy helps mitigate operational risks such as poor access controls and data loss	5.32	1.01	.70		
Data strategy improves IT infrastructure and reduces data costs	5.41	1.00	.79		
Data strategy helps develop analytical and digital capabilities	5.61	.95	.80		
Data strategy helps to improve data quality (integrity, precision, accuracy)	5.54	.95	.75		
Data strategy helps streamline multiple sources of data and information	5.51	.93	.73		
Big data knowledge management				.93	.68
Our firm uses coding systems of big data that we have collected about our customers using social media.	5.55	1.02	.82		
Our firm uses internal mechanisms to promote exchange of big data/ information on customers.	5.51	.93	.86		
Our firm uses participatory techniques among our employees and customers (such as client meetings, and client interviews for improvements).	5.50	.97	.82		
Our firm has information processing systems to process big data about customers.	5.60	.95	.82		
Our firm uses control systems and reviews the firm's existing information on customers.	5.47	.90	.85		
Our firm uses systems that allow the big data that were used in previous innovation tasks to be used in new innovation tasks.	5.52	.88	.77		
Big data analytics capabilities				.82	.60
Data visualization skills	5.15	.98	.74		
The ability for the contextual recommendation	5.32	.99	.73		
Expertise in handling IT systems/ software and the use of data	5.62	.96	.85		
Sustainability marketing				.92	.53
Our hotel provides a wide range of sustainable products or services	5.46	.94	.68		
Our hotel adopts a high proportion of sustainable products or services	5.46	.96	.67		
The prices of sustainable products or services launched by our hotel are competitive in the market	5.31	1.03	.71		
Our hotel launches sustainable products or services that customers can afford	5.45	.97	.75		
The price increase of the sustainable products or services is consistent with the market price	5.21	1.06	.61		
If customers choose sustainable products or services, we will give discounts	5.51	.98	.63		
We will launch different sustainable products or services based on different markets	5.54	.96	.74		
The sustainable products or services have good profitability	5.38	1.02	.80		
We will launch new promotional programs for sustainable products or services	5.47	.94	.81		
The sustainable products or services launched by our hotel are recognizable	5.37	1.03	.84		
We promote sustainable products or services through different marketing tools	5.45	1.04	.85		
Competitive advantage				.86	.51
Data strategy enables the organization to gain a clearer insight into the consumer market and business opportunities	5.56	.97	.70		
Data strategy enables people to think about changes to leverage the performance of their organization	5.61	.87	.68		
Data strategy enables the organization to be more responsive than its competitors	5.59	.98	.65		
Data strategy enables the organization to make decisions faster and more reliably	5.70	.99	.78		
Data strategy enables competitive differentiation through innovation	5.60	.89	.74		
In general, we are more successful than our competitors	5.47	1.00	.73		
Profitability				.77	.53
Increase profits through big data sustainable marketing	5.57	.92	.69		
The return on investment can be improved through big data sustainable marketing	5.60	.93	.82		
Market efficiency can be improved through big data sustainable marketing	5.64	.99	.67		
Sales volume				.78	.54
Sales can be increased through big data sustainable marketing	5.55	1.03	.81		
Market share can be changed through big data sustainable marketing	5.48	.99	.68		
Get more new customers through big data sustainable marketing	5.58	.97	.70		
Intangible market assets				.75	.51
Improve customer satisfaction through big data sustainable marketing	5.58	.89	.66		
Promotion of customer loyalty/ willingness to revisit through big data sustainable marketing	5.53	1.02	.73		
Brand image can be enhanced through big data sustainable marketing	5.59	.95	.74		
Proactive social media orientation				.80	.50
Our firm helps customers to anticipate developments in the markets using social media.	5.52	.98	.61		
Our firm continuously tries to discover additional needs of our customers of which they are unaware using social media	5.51	.97	.77		
	5.53	.98	.63		

(*continued on next page*)

Table 2 (*continued*)

Constructs and items	Mean	S.D	Factor loading	CR	AVE
Our firm innovates using social media even at the risk of accelerating our products obsolescence.					
Our firm searches for opportunities to use social media in areas where customers have difficulty expressing their needs.	5.49	.92	.80		
Social media customer collaboration				.93	.79
Our firm interacts with customers to obtain useful information for innovation using social media.	5.62	.90	.87		
The intensity with which our firm interacts with customers using social media is high.	5.57	.94	.91		
Our firm frequently uses social media to organize meetings with customers.	5.43	1.04	.87		
The number of customers with whom our firm interacts using social media is high.	5.48	1.00	.90		

indicates an acceptable fit ($\chi2 = 349.441$, $p < .001$,$\chi2/df = 4.111$, CFI = 0.963, NNFI = 0.951, RMSEA = 0.078). Finally, as suggested by Fornell and Larcker (1981), all the factor loadings should be higher than 0.7, but higher than 0.65 is also acceptable (Matzler, Renzl, Müller, Herting, & Mooradian, 2008). All the factor loadings are greater than 0.65, confirming the convergent validity of the structure (Hui & Wan, 2003). Table 3 summarizes the mean, standard deviation and correlation of each variable. All the correlations are significant, and the value of the variance inflation factor (VIF) is below 10, the cutoff recommended by Li and Liu (2018), which indicates that collinearity does not exist in the current research.

4.1.2. Hypotheses test

In Fig. 2, we show all the standardized path coefficients, and the overall structural model shows a good model fit ($\chi2 = 1041.432$, $p < .001$, $\chi2/df = 3.857$, CFI = 0.936, NNFI = 0.935 GFI = 0.847, RMSEA = 0.072). Thus, the proposed model is suitable for Hypothesis development.

In Fig. 2, all direct paths are significant. H1a and H1b state that big data knowledge management mediates between offensive data strategy and big data analytics capabilities and between defensive data strategy and big data analytics capabilities. The results indicate that the average indirect effects of an offensive data strategy on big data analytics capabilities through big data knowledge management ($\beta = 0.165$; $p < .001$) and of a defensive data strategy on big data analytics capabilities through big data knowledge management ($\beta = 0.325$; $p < .001$) are significant. Moreover, the 95% bootstrap interval does not contain zero (Zhang et al., 2019). Thus, H1a and H1b are supported.

H2 proposes the mediation of sustainable marketing. The results show that sustainable marketing significantly mediates the effects of big data analytics capabilities on competitive advantage ($\beta = 0.654$; $p < .001$), and the 95% bootstrap interval does not contain zero, which supports H2. H3a, H3b and H3c also suggest a mediating role of sustainable marketing. Based on our results, the indirect effects of big data analytics capabilities on profitability ($\beta = 0.54$; $p < .001$), sales volume ($\beta = 0.65$; $p < .001$), and intangible market assets ($\beta = 0.46$ $p < .001$) through sustainable marketing are significant, and the 95% bootstrap interval does not contain zero. Thus, H3a, H3b and H3c are statistically supported. In summary, in Table 4 shows the 95% bootstrap confidence intervals of indirect effects do not contain zero which indicates that the mediation hypotheses in this study are all supported.

H4a and H4b refer to the moderators of proactive social media orientation and social media customer collaboration, respectively. In Table 5, model 2 shows that the coefficient for the interaction term of sustainable marketing*proactive social media orientation is positive and significant for competitive advantage ($\beta = 0.041$; $p < .001$). Furthermore, the moderating role of social media customer collaboration significantly influences the effects of sustainable marketing on intangible market assets ($\beta = 0.061$; $p < .001$) in model 4. In Figs. 3 and 4, we use a simple slope test and draw a two-dimensional diagram to examine interaction effects. H4a and H4b are found to be supported.

In the full three-step and constrained model (Ping, 1995), the results indicate that PSMO (.25, $p < .001$) and SMCC (0.35, $p < .001$) as well as two interaction terms, SM × PSMO (0.02, $p < .05$) and SM × SMCC (0.02, $p < .05$), had significant relations with competitive advantage and intangible market assets ($\chi2 = 990.458$, $p < .001$, $\chi2/df = 3.695$, CFI = 0.945, NNFI = 0.951 GFI = 0.887, RMSEA = 0.072). Likewise, in the unconstrained model, the results indicate that PSMO (0.25, $p < .001$) and SMCC (0.35, $p < .001$) as well as two interaction terms, SM × PSMO (0.02, $p < .05$) and SM × SMCC (0.02, $p < .05$), and the 'samesource' factor ($p < .01$) had a significant association with competitive advantage and intangible market assets ($\chi2 = 763.68$, $p < .001$, $\chi2/df = 3.36$, CFI = 0.945, NNFI = 0.941 GFI = 0.89, RMSEA = 0.072). In comparing steps 2 and 3, using the method devised by MacCallum and Mar (1995), the third step in both the constrained and unconstrained models explained an additional 7 percent of variance beyond that explained by earlier steps.

The results of the single-indicant latent-variable interaction approach were consistent with the hierarchical regression analysis. This study followed Ganzach's (1997) hierarchical procedure for SEM testing to estimate whether the inclusion of main and interaction effects is empirically meaningful. These results verify that the strengths of the Hypotheses 4a and 4b paths were consistent and supported across the hierarchical regression and single-indicant latent-variable interaction

Table 3
Means, standard deviations, correlations and reliability.

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	VIF
Offensive data strategy	5.55	.71	**(.86)**											2.27
Defensive data strategy	5.41	.72	.75***	**(.87)**										3.19
Big data knowledge management	5.51	.72	.68***	.68***	**(.89)**									3.89
Big data analytics capabilities	5.36	.81	.76***	.59***	.61***	**(.78)**								5.51
Sustainability marketing	5.42	.75	.72***	.73***	.71***	.61***	**(.92)**							3.83
Competitive advantage	5.59	.72	.77***	.75***	.74***	.59***	.80***	**(.86)**						4.28
Profitability	5.60	.81	.70***	.66***	.74***	.54***	.70***	.74***	**(.82)**					3.25
Sales volume	5.54	.86	.66***	.61***	.65***	.54***	.67***	.69***	.76***	**(.82)**				2.24
Intangible market assets	5.56	.81	.67***	.65***	.74***	.56***	.67***	.71***	.72***	.74***	**(.83)**			2.56
Proactive social media orientation	5.51	.79	.65***	.59***	.81***	.60***	.65***	.68***	.65***	.62***	.63***	**(.84)** ***		2.25
Social media customer collaboration	5.53	.77	.53***	.51***	.72***	.48***	.67***	.64***	.62***	.61***	.61***	.73***	**(.81)** ***	1.25

Note: ***P < .001; Cronbach's alpha values are shown on the diagonal in bold.

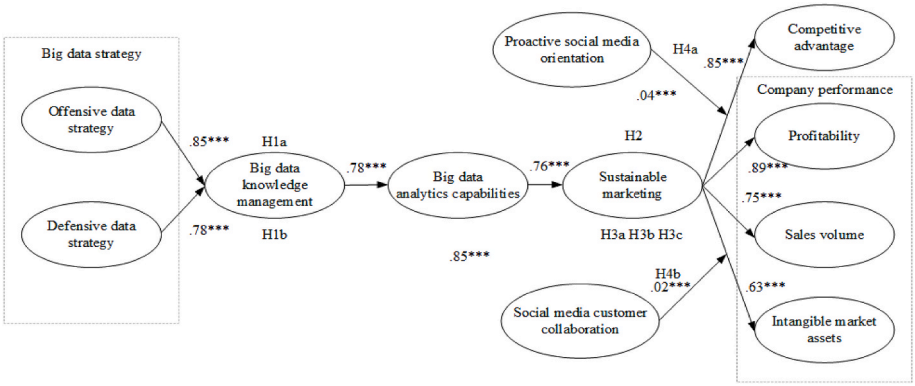

Fig. 2. Proposed research framework-Results.

Table 4
Mediating effect test for H1a to H3c.

Hypothesis path	Bias-corrected 95% CI				Percentile 95% CI		
	Standard error	Estimates	Lower	Upper	Lower	Upper	Results
H1a	.05	.14***	.049	.24	.04	.24	Support
H1b	.06	.20***	.1	.34	.09	.33	Support
H2	.057	.32***	.22	.45	.21	.44	Support
H3a	.048	.35***	.25	.46	.24	.45	Support
H3b	.048	.22***	.14	.33	.13	.33	Support
H3c	.044	.13***	.06	.24	.05	.22	Support

*P < .05; **P < .01; ***P < .001.

Table 5
Results of the moderator test with H4a and H4b.

Variables	Competitive advantage				Performance			
	Model 1		Model 2		Model 3		Model 4	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Intercept	2.88	9.26***	3.77	6.92***	.168	1.44	.291	2.42***
Control variables								
Gender	.186	2.66*	.17	2.49*	.01	.64	.01	0.32
Age	-.1	3.71***	-.1	−3.82	.023	−0.24	0	2.2*
Education	.13	.37	.06	−1.27	.02	1.96*	.02	1.95*
Independent Variables								
SM	.62	13.30***	.45	2.02*	.51	7.90***	.63	1.99*
PSMO	.27	5.81***	.11	2.00**				
SMCC					.37	4.89***	.42	1.98*
Interaction								
SM*PSMO			.03	1.99*				
SM*SMCC							.03	1.99*
Model statistics								
R2	.82		.82		.71		.71	
R2adg	.68		.68		.50		.50	
F	268.97***		179.09***		126.73***		84.25***	

*P < .05; **P < .01; ***P < .001; SM = sustainable marketing; PSMO = proactive social media orientation; SMCC=Social media customer collaboration.

analyses.

4.1.3. Robustness checks

To verify the robustness of the statistical results, we follow the recommendations for robustness testing commonly adopted in tourism and hospitality journals (Ruan, Li, Zhang, & Liu, 2020; Zhang. et al., 2021). First, 2 subdimensions of big data strategy were synthesized into a second-order dimension in an alternative model. Second, 3 subdimensions of company performance were merged into a second-order dimension in an alternative model. Third, the structural model was used to examine the overall model fit and path of the alternative model. Finally, the proposed model was compared to two alternative models to examine path coefficients, mediation effects, moderation effects and model fit.

The results show that the model fit of the alternative model is worse than that of the proposed model ($\chi 2 = 1791.362$, $p < .001$; $\chi 2/df = 3.083$; CFI = 0.88; NNFI = 0.85, RMSEA = 0.11) (see Fig. 5). Thus, the proposed model is robust.

4.2. Qualitative results: study 2

Application of a mixed-method design can make quantitative results more comprehensive and rigorous and lead to more in-depth discoveries (Pham et al., 2019). After the interviews, the transcripts were read by the researcher and discussed with the research team to determine the corresponding context. To protect the privacy of the interviewees, each interviewee was coded with a number.

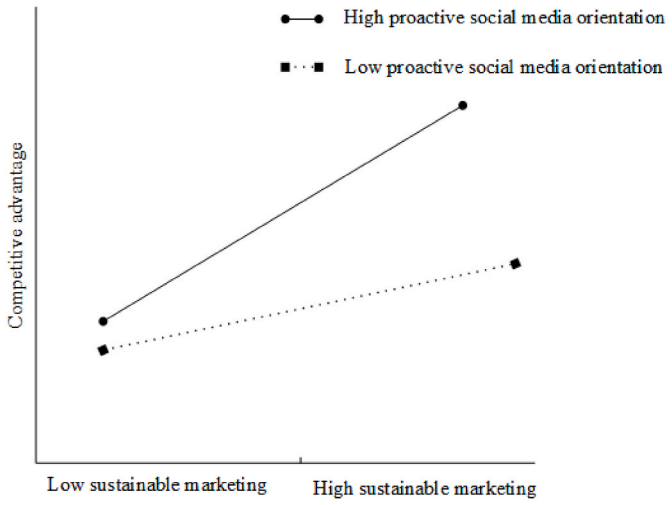

Fig. 3. Moderation results of proactive social media orientation.

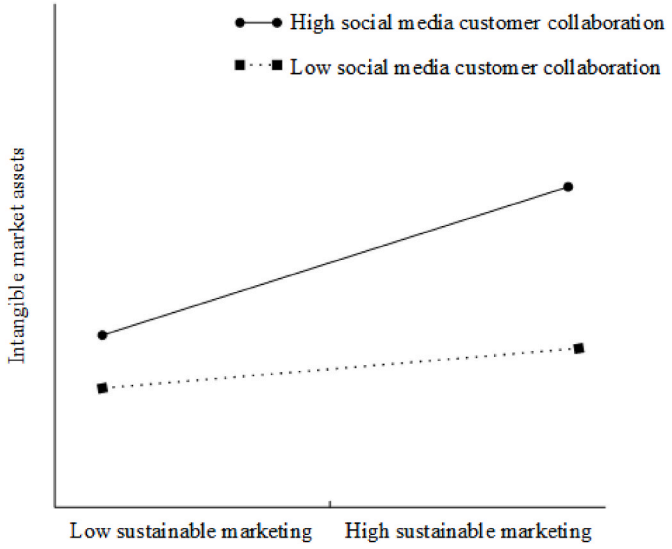

Fig. 4. Moderation results of social media customer collaboration.

4.2.1. Formation of big data analytics capabilities

From a resource-based perspective and DC theory, the development of a hotel's big data analytics capabilities can result in a competitive advantage (Akter, Gunasekaran, Wamba, Babu, & Hani, 2020; Hossain, Akter, & Yanamandram, 2021). Organizational strategy and knowledge management are essential to improving big data analytics capabilities (Mangla, Raut, Narwane, Zhang, & Priyadarshinee, 2021). Therefore, hotels should improve big data analytics capabilities from a strategic perspective.

- *"In the future, the head office will set up an IT computer department to integrate the data of all of its hotels and organize related training courses to enhance employees' data analysis capabilities."* (R6, man)
- *"We are an international brand, but currently each department has its own database. At present, the headquarters is trying to connect the databases. The integrated database will be helpful for the implementation of various strategies in the future."* (R15, man)

There are two types of big data strategies. The defensive data strategy focuses on the integration of data within the enterprise and improves operational efficiency through internal data analysis.

Our digitization level exceeds the imagination, not only for consumers but also for internal management. For example, water, electricity and air conditioning for an entire hotel can be managed with a single console. (R16, man).

The offensive data strategy aims to analyze external data. In the service industry, consumption records and purchasing behavior are used as data sources. The CRM system can be used to understand consumers' profiles, consumption habits, and customer preferences and to predict future consumption behavior.

- *Our CRM system currently manages hundreds of thousands of data records that record the preferences of consumers around the world. For example, if you have stayed at a hotel of our group in Shanghai, we know what type of room you like and what beverages you like to drink. On the other hand, the membership system also stores our CRM data. From this information, we can repeat promotions for members."* (R15, man)
- *"From a strategic view, you need to understand how to use data across platforms. You need to determine from the data which ones can do cross-selling. For example, guests from Taipei who stay at the hotel may also go to the hotel restaurant in the future."* (R8, man)

Knowledge management is critical to improving big data analytics capabilities. In the early stages of promoting big data, organizations face many technical obstacles. The classification and storage of relevant knowledge through a knowledge management system and exchange and sharing between members can promote the overall big data analytics capabilities of an organization.

- "Thirty-five percent *of our company's employees can do all of their work as long as they have access to the Internet. Our company uses a platform-based approach to store, communicate, and disseminate knowledge to improve the efficiency of knowledge sharing within the team is, and information can also be accumulated for horizontal and cross-departmental communication.*" (R3, man)

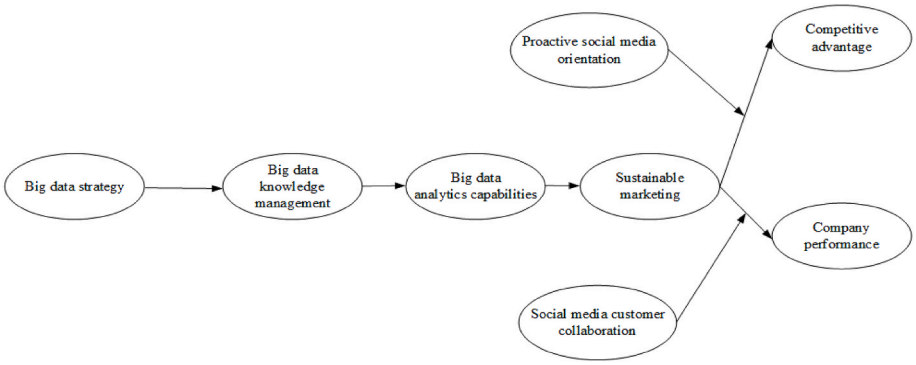

Fig. 5. Alternative model to confirm the original model is appropriate to further examinations.

- "*Our unit adopts some standard operating procedures, such as on how to develop strategies for product design or how to plan through the food and beverage department. These processes follow a fixed model, and new entrants can also refer to these processes to get started quickly.*" (R9, man)

4.2.2. Big data analytics capabilities enhance competitive advantage and company performance through sustainable marketing

From a resource-based perspective, when a company invests more resources in the development of big data, the marketing capabilities are enhanced when companies apply big data to marketing, which in turn leads to better company performance (Suoniemi et al., 2020).

- "*We can use big data analysis to determine why a product is not selling well. For example, if the bounce rate is too high, it may be that our landing page is not attractive. After identifying the reason, we modify the layout and UX and UI design of the landing page, which truly helps improve performance.*" (R18, woman)
- *"To put it simply, I think the most important application of big data in the hotel industry is that of customer data analysis. We use big data to study consumer behavior and launch customized products."* (R17, woman)

4.2.3. Effects of social media on big data marketing

Social media plays an important role in tourism industry marketing (Hysa, Karasek, & Zdonek, 2021). Due to the interactivity, social media are regarded as a channel for establishing customer relationships and communication. The popularity of the Internet and various social software has allowed organizations to secure more channels through which to reach consumers (Hysa et al., 2021). The application of social media in marketing can lead to better sales performance (Ibrahim, Aljarah, & Sawaftah, 2021; Gaffar, Tjahjono, Abdullah, & Sukmayadi, in press).

- "*Social marketing truly improves performance. For example, a particular Internet celebrity runs a Facebook club with approximately 40,000 members. We designed an exclusive promotion plan for his fans, and every time it is offered, it is immediately sold out.*" (R8, man)
- "*We have invited key opinion leaders (KOLs) to live auctions, and we act as customer service staff to help deal with customer issues. Inviting the right KOL is indeed a great help to performance.*" (R17, woman)

4.2.4. Qualitative research findings

According to the interview results, a hotel's big data analytics capabilities are related to competitive advantages and company performance. First, most hotels have built ERP or CRM systems and have tried to integrate databases from a strategic view to improve their big data analytics capabilities. Second, defensive big data strategies and offensive data strategies are key to developing big data analytics capabilities. For hotels, an ERP system can be regarded as a defensive data strategy, and CRM can be classified as an offensive strategy. Third, the promotion of knowledge management results in the proper classification and storage of knowledge within an organization, which is helpful for knowledge accumulation. Fourth, a marketing plan developed from the results of big data analysis can better satisfy customers and improve organizational performance. Finally, the use of social media marketing can enhance the effectiveness of marketing campaigns. The results of qualitative analysis not only provide us with a deeper understanding of the process of big data marketing in the hotel industry but also further confirm the results of the quantitative analysis.

5. Discussion and conclusion

Based on the KBDCs, this research combined quantitative and qualitative methods to clarify different types of big data strategies from offensive and defensive to big data analytics capabilities and to verify the internal link between big data and sustainable marketing. To date, such integrated and complex frameworks have rarely been proposed or examined. Importantly, the findings of this study are not only consistent with assumptions but also yield new results that diverge from those of prior studies. The following important conclusions are drawn.

First, the current study confirms the positive relation between big data and competitive advantage. In particular, we extend and explore the mechanisms between variables in depth. Previous studies have proven that big data strategies have a positive effect on company performance (Medeiros et al., 2020). Since past studies have oversimplified the relationship between big data and performance, the mechanism from big data to performance must be further clarified. According to the KBDCs, to promote big data, it is necessary to improve capabilities, and knowledge management plays an important role in enhancing big data analytics capabilities. Finally, the development of big data analytics capabilities leads to improvements in marketing capabilities and to an enhanced competitive advantage.

Second, big data knowledge management, sustainability marketing, proactive social media orientation and social media customer collaboration are essential to enhancing competitive advantage and company performance in the hotel industry. This research determined the core elements involved from the big data process to social media management and clarifies their roles. Specifically, big data knowledge management helps to improve big data analytics capabilities. Furthermore, big data analytics capabilities serve as a bridge between organizational big data strategies and marketing performance. In other words, if an organization wants to use big data to improve sustainable marketing performance, big data analytics capabilities are essential. An organization's improvement of big data analytics capabilities is attributed to the integration of big data into strategic planning and the implementation of knowledge management.

Third, our results demonstrate how proactive social media orientation promotes competitive advantage, while social media customer collaboration promotes intangible assets. The effects of proactive social media orientation and social media customer collaboration on sustainability marketing can create a competitive advantage and intangible assets. Notably, social media operations can magnify the effects of marketing programs. This result further responds to the views of past research and extends to the hotel industry and sustainable marketing (Tanford et al., 2020).

5.1. Theoretical contribution

This research makes several contributions to theories of hospitality management. First, this study confirms that different big data strategies, defensive and offensive, have different functions for enterprises. While most previous studies emphasize offensive strategies (DalleMule & Davenport, 2017; Medeiros et al., 2020), this study finds that both strategies are important for shaping big data analytics capabilities. Defensive strategies emphasize the internal efficiency of an enterprise, while offensive strategies emphasize interactions with external customers. Second, this study combines the knowledge-based and dynamic capabilities perspectives to explore the relationship between big data capability formation and sustainable marketing. Most past research has been based on a single theory, such as resource-based (Suoniemi et al., 2020), knowledge-based (Nguyen et al., 2015), and DC theories (Chierici et al., 2019). Research on KBDCs has yet to receive full attention from the hotel industry (Shamim et al., 2021; Sharmin et al., 2021) or professional service firms (Khaksar et al., 2020, pp. 1–18). Shamim et al. (2021) found that big data management capabilities lead to high online quality ratings through the mediation of knowledge creation and service innovation based on KBDCs in the hotel industry. Consistent with Shamim et al. (2021), this research explores the relationship between big data strategies and big data analytics capabilities. However, the difference from Shamim et al. (2021) is that they focus on knowledge creation, which is the result of big data management capabilities. This research regards big data knowledge management as a strategy to improve employees' big data analytics capabilities (Khaksar

et al., 2020, pp. 1–18). Moreover, the relationships between big data management capabilities, knowledge management and service management are explored in Sharmin et al. (2021). This research further extends the model to sustainable marketing and social media markeing and extends the applicability of KBDCs in the hotel industry. Finally, most previous studies on big data have focused on the relationships between big data and competitive advantage (Shan, Luo, Zhou, & Wei, 2019; Medeiros et al., 2020) and performance (Gupta, Drave, Dwivedi, 2020; Mandal, 2018), but the key factors behind the improvement in competitiveness and performance must be further explored. Theoretically, this study uses sustainable marketing as a mediating variable between big data and competitive advantage and performance, indicating that sustainable marketing can help companies achieve profitability and improved competitiveness. In addition, the application of social marketing has revealed that different social media strategies have different effects on competitive advantage and corporate performance. Furthermore, Khaksar et al. (2020) suggested that KDBCs could be categorized into knowledge acquisition capabilities, knowledge generation capabilities, and knowledge combination capabilities and that all three knowledge-based dynamic capabilities can enhance perceived knowledge worker productivity. We found that knowledge management is also an important key factor in the development of big data analytics capabilities. This result is consistent with Khaksar et al. (2020, pp. 1–18).

5.2. Managerial implications

The findings of this study not only provide theoretical guidance but also have implications for hotel practitioners regarding how to effectively improve competitive advantage by promoting big data. First, our results confirm that a distinctive big data strategy not only is beneficial to big data analytics capabilities but also stimulates competitive advantage and performance. Hotel's utilization of big data can be regarded as digital transformation (Pappas et al., 2018) and value creation (Danilo Pesce, Neirotti, & Paolucci, 2019). Pappas et al. (2018) conceptualize big data and business analytics ecosystems and propose a digital transformation and sustainability (DTS) model that portrays how big data and business analytics ecosystems can pave the way toward digital transformation and sustainable societies. Danilo Pesce et al. (2019) enriches our understanding of what strategies digital platforms adopt to create value in big data contexts and provides a base to continue the investigation of other ecosystems driven by big data. Different types of big data strategies have various effects on organizations, but they can all improve big data analytics capabilities. The defensive data strategy emphasizes the improvement of internal processes and operational efficiency. Therefore, for hoteliers, the quality of internal decision-making can be improved by integrating a database or flattening the organizational structure to shorten the decision-making process and increase the response speed (Arasli, Alphun, & Arici, 2019; Joseph & Gaba, 2020). The offensive data strategy focuses on customer data analysis, which is particularly important in the service industry. Hotels can learn about customers' profiles through different channels, such as through CRM, social media, and membership management, and plan different marketing plans for different consumers to improve performance (Duan, Yu, Cao, & Levy, 2016; Kim & Chae, 2018; Trainor, Andzulis, Rapp, & Agnihotri, 2014). Second, big data capability directly enhances sustainable marketing. Consequently, hotel practitioners should consider ways to promote big data analytics capabilities. Our research suggests that knowledge management is crucial to improving big data analytics capabilities. When a hotel promotes a big data strategy, whether employees have sufficient capacity to implement it is essential. For example, when a hotel introduces membership management, employees must be able to operate the new system and interpret data reports. Education and training can be used to familiarize employees with new operating procedures or to encourage employees to learn new skills related to big data through the performance appraisal system. Companies can also use benchmarking to communicate with hotels in the industry that have successfully implemented big data. In addition, Elsharnouby and Elbanna (2021) stated that hotels operators need to develop dynamic marketing capabilities in highly dynamic environments. For example, learn about customer needs and channel members, discover competitors' strategies. These capabilities have been shown to directly impact a hotel's competitive advantage. The hotel regional headquarter may provide data to the regional hotel branches. The regional hotel enable perform the classic marketing activities in an insightful and data-driven manner. Third, managers need to be aware that social media can indeed improve the effectiveness of marketing programs. Therefore, hotels can choose to operate suitable social media platforms based on the target group. For example, the new luxury brand MOXY 's target market is luxury youth hostels, and its main customers are Generation Z individuals (Han & Lee, 2021). Therefore, its social media are primarily based on Instagram. When focusing on short-term sales performance, collaborations with Internet celebrities can be used to provide promotional programs that provide fans with exclusive discounts (Touni, Kim, Choi, & Ali, 2020). As Gallego and Font (2021) pointed out, during the COVID-19 pandemic, different levels of administration can use big data to avoid duplication of work and effectively revitalize the hotel and tourism market. Therefore, for managers, this research can help them optimize business processes to take advantage of new opportunities. The rise and development of big data has brought great opportunities to the industry, but the ability to extract value from big data depends on the vision and relevant knowledge of managers. This article can be used as an important guide for managers to comprehend the reality of big data in the hotel industry and determine its potential value for their firms.

5.3. Limitations and future research

Although this study systematically clarifies the relationship between big data analytics capabilities and hotel marketing, this work is affected by limitations that require further exploration in future studies. First, this research confirms the mechanism formed by big data analytics capabilities in organizations and verifies the relationships between big data analytics capabilities, sustainable marketing, competitive advantage, and organizational performance. However, this study uses only a hotel industry sample to verify the theoretical model. Whether the same mechanism can be empirically demonstrated in other industries remains to be verified. In addition to using the resource- and knowledge-based perspectives, the factors that form big data analytics capabilities can be discussed based on different theories, such as sociomaterialism theory (Upadhyay & Kumar, 2020) and organizational information processing perspective theory (Yu, Zhao, Liu, & Song, 2021). Furthermore, although this research uses quantitative and qualitative research methods, the deviation of a single analysis method can be reduced (Bryman & Bell, 2011). Follow-up research can collect longitudinal data to examine the impacts of big data analytics capabilities on organizations. Finally, this study adopted subjective measurement for company performance. Although there are still most studies using subjective measurement in hospitality studies, the objective measurement of company performance can be included in future work. which can further reduce the CMV due to multi-source data.

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