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Growth of digital brand name through customer satisfaction with big data analytics in the hospitality sector after the COVID-19 crisis

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ABSTRACT

This study examines the best practices for the optimization of the corporate digital brand name by taking into consideration customers' behavioral big data and web analytics. In the first stage of the study, customers' satisfaction big data have been extracted with the assistance of a web scrapping tool from TripAdvisor for 189 hotels in Hubei province, and behavioral data from Hubei province hospitality websites have been gathered with the assistance of web analytics platforms for 5.7 million website visitors for the last 18 months. In the second stage of the research, those data have been statistically analyzed including descriptive, correlation, and regression analysis. Then, a fuzzy cognitive map has been created to present the intercorrelation between the parameters and two optimization scenarios have been developed for digital brand name and customer satisfaction. Finally, an Agent-based model has been created in order to simulate the customers' behavior in the corporate website and TripAdvisor. The results indicated that hotels in Hubei province need to invest less in social media advertisements than search engine advertisements in order to achieve a competitive advantage and improve their digital brand name. Additionally, hotels need to develop their websites with more engaging content to maintain the customer on the corporate website for more time in order to optimize customer satisfaction in contrast to healthcare and libraries websites.

Introduction

The COVID-19 pandemic forced all destinations to introduce travel restrictions, with airplanes on the ground and hotels, restaurants and travel agencies closed, making the Hospitality, Travel and Tourism (HTT) sector one of the worst affected with tremendous economic losses (Obembe et al., 2021). The World Tourism Organization has released the 11th and last one report on travel restrictions on 26th November 2021 (UNWTO, 2021), stating that 98% of all destinations have some kind of travel restrictions in place. As of 2 November 2022, where there have been 628.035.553 confirmed cases of COVID-19 globally (WHO, 2022), most countries have lifted their travel bans. This new situation, while it offers a pandemic relief, it simultaneously provokes the public opinion to be split over this policy (Stoeckel et al., 2022). Given the great number of confirmed cases, this dichotomy raises concerns on how risk perception contributes to the adoption of new patterns of behavior after severe outbreaks familiarity (Sakas et al. 2021).

Zajenkowski et al., (2020) state that during novel crisis, such as the Covid-19 pandemic, people perceptions are more likely to be influenced by situational cues, rather than personality traits. Although the research is geographically limited in one country, it is an important outcome which further supports the research of Moya et al., (2020) regarding customers' extensive behavioral change as a consequence of crisis situations. As the public opinion has changed throughout the stages of the pandemic (Mahdikhani, 2022), so does the digital behavior of online users (Sakas et al., 2022a), pushing companies over the technology tipping point (Nasir et al., 2022). Especially for the HTT ecosystem, tourist behavior has been changed due to travel and mobility limitations, psychological and economic factors (Marques Santos et al., 2020). Cognitive, personality, and affective factors would predict travel behavior and travel preferences during the COVID-19 pandemic (Morar et al., 2021).

Acknowledging online users' needs is no longer enough since customers have changed their information-seeking process and expect a high-quality digital experience that combines all brand's touchpoints (Vannucci & Pantano, 2020). With the advancement of technology, HTT

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organizations have less opportunities to create strong emotional bonds with online users and improve customers satisfaction levels, since the human-touch aspect in services is absent during the customer digital journey (Kandampully & Solnet, 2020). The success of HTT organizations relies on the optimization of the digital journey as the cornerstone of an efficient multichannel communication strategy (Hu & Olivieri, 2021), having a human-centered perspective (Bonfanti et al., 2021). The industrial revolution 5.0 offers deep insights on how to understand, evaluate and predict customers' online behavior, which in turn affects brand positioning and marketing activities (Pillai et al., 2021).

Ward (2020) state that social theory is able to explore the implications of Covid-19, recommending futures studies on social media and other platforms. Based on Sahed et al. bibliometric analysis (2021), social media marketing is the second-largest research cluster of digital marketing literature. To this end, the current paper focus on analyzing the behavior of online users, focusing on Hubei province hospitality websites metrics and Tripadvisor's reviews for the optimization of the corporate digital brand name. Branding in the HTT sector has been the point of several researches (Vila et al., 2021;). The tourism and hospitality sector in Wuhan has been extensively researched within the academia (Zhang et al., 2022). However, the digital transformation of the HTT sector heavily relies on customers' behavior in response to a potential crisis (Sigala, 2020). In this vein, the current paper attempts to analyze customers' digital behavior on Wuhan's hospitality sector based on big data and web analytics with the intention to offer guidelines on how to develop a solid brand communication strategy that will perform efficiently during crisis situations.

The novelty of the paper relies on the employment of a dual statistical analysis of users' online behavior, based on websites' user engagement metrics and Tripadvisor's reviews, in an attempt to predict trends but also to collect emotions and capture sentiments via the use of web analytics on social media (Chatterjee, 2020). This will enable companies within the HTT ecosystem to understand customers' online behavior through their interaction with the website and measure customers' satisfaction via the analysis of reviews.

The paper proceeds as follow: First, the theoretical background is presented. In this section, the related literature leads to the research hypothesis and the development of the conceptual framework. The paper then analyzes the materials and methods used along with the results of the estimation techniques used. Moreover, the discussion section analyzes in depth the finding of the study to follow the conclusion of the study including the various implications of the findings. Finally, the research limitations and future research recommendations are presented.

Conceptual framework

Behavioral psychology in e-commerce customer journey

Having its roots in digital psychology, understanding customers' psychological behavior is currently a rapidly growing field that shapes an organization's brand reputation and credibility (Mustapha et al., 2022). Especially after the widespread of the pandemic, which has forced users to employ creative methods in order to cope with stressful situations, leaving psychological scars (Ansar & Goswami,2021), harnessing the power of psychology creates both challenges and opportunities for marketers. Unlike automated systems, whose functioning is programmed on strict logical lines, customers' digital purchasing intention and referrals are greatly influenced by the psychological customer engagement (Bozkurt et al., 2022). In order to utilize social psychology and provide the emotional touch needed during the development of an effective brand communication strategy, managers need to understand the concept behind design psychology as well as the phycological principles that affects the digital user journey (Kuehnl et al., 2019). The analysis of customers' psychological processes will enable marketing managers to create, reinforce and maximize valuable shopping memories, that will in turn lead to higher levels of customers' engagement (Myoung-a & Sang-Lin, 2020).

Multiple researches have been devoted to psychological principles in an attempt to facilitate the digital customer journey. The analysis of behavioral attitudes within the HTT ecosystem based on the Zeigarnik effect seem to have raised the interest of the academia (Sasaki et al., 2020). Bauer et al. (2022) analyze the Zeigarnik effect, in which customers tend to remember more their unfinished actions than the finished ones. By using this effect, customers are effectively motivated to proceed to task completion through progress bars, gamification and rewards (Tokmak, 2019).

Nowadays, customers' digital journey is much more complex, with numerous touchpoints and channels, from the awareness to the loyalty stage, making the decision-making process of marketing managers a tough task (Yachin, 2018). Customers' online behavior has changed during Covid-19 and the overwhelming information makes users' experience even more complicated (Baharom et al., 2020). Proctor and Schneider (2018) investigate Hick's Law, in which the amount of time that the users need in order to make their decision depends on the number of options available. In essence, the more the options, the longer for users to decide. The authors encourage more researches on human-computer interaction using new technologies. Roetzel (2019) further states that the in-depth analysis of online users' information search, selection, processing and evaluation plays an important role in their decision-making process. In this regard, Ismaili (2020) suggests graphical representations of mental models to improve the overall comprehension level of online users and simplify their decision-making process.

The literature review further reveals the psychological principal of Miller's Law, in which the human mind can only handle seven pieces of information when it comes to memory and processing, making visualization of marketing data a solution for marketing managers (Umesh & Kagan, 2015). Consumers may have the power and access to a wide spectrum of information and online reviews but the improvement of their decision-making process comes via reducing information overload (Hu & Krishen, 2019). Moreover, an interesting study has been conducted by Mufti et al. (2018) in which the Von Restorff effect proves to have an extensive impact on customers' behavior and purchasing intention, implying that among similar objects, the one that stands out due to its color, 3D animations and other characteristics is more likely to be remembered by users.

Ultimately, information overload damages decision quality (Peng et al., 2021) and by extension their online purchasing behavior, a fact that raises concerns on how companies should develop their brand communication strategy. Flowing too much information to users has a tremendous impact on their pre-travel behavior (Tan & Kuo, 2019). Online users evaluate negatively the explosion of information (Magnini & Dallinger, 2018), a fact that opens new avenues on how the HTT sector will gain from fostering excellent user experience while simultaneously retaining strong emotional relationships during the current digital explosion of Industry 5.0. The analysis and investigation of behavioral psychology principles greatly contributes to the advancement of the existing knowledge on major corporate issues, such as why people behave in a certain way while shopping online, how behavior can be predicted, changed or even prevented.

User experience & customer satisfaction in the htt sector: the big data challenge

The recovery process for the HTT sector has already started with most countries to currently developing measures so as to build a post Covid-19 resilient tourism industry (Škare et al., 2021), as a digital transformation pioneer (Padro & Ladeiras, 2020). The new economic development embraces the advancement of technological transformations and Industry 5.0 towards human centricity (Zizic et al., 2022), making the HTT industry one of the early adapters of new technology and platforms (Okafor et al., 2022). The pandemic has accelerated the transition to more sustainable models of tourism. Mensah and Boakye (2021) propose that the sustainability of the tourism industry should be based on the use of digitalization and social media. As these two factors are able to propel the travel experience and customers satisfaction in a way that contributes to sustainability, the tourism industry will revitalize and recover in a faster pace (Gagan et al., 2021).

The digital boom has greatly evolved the customer journey by adding new touchpoints, such as websites, blogs, social media, chatboxs and others (Mele & Russo-Spena, 2022). This is important considering that brands now have a better control on customers' experience by building a muti-channel approach that supports personalization (Sakas et al., 2022a). Given that the HTT industry is at the forefront of Industry 5.0 Revolution, with personalized service and the use of big data for up-to-date information of customer preferences to be some of the key elements (Pillai et al., 2021), the hospitality sector need to be adapted to the existing technology so as to provide flexible and resilient services.

The growing attention of e-tourism represents a new approach to the kind of experience delivered to online users and manifests along all stages of the digital customer journey (Pencarelli et al., 2021). HTT companies need to go the extra mile to meet the expectations of online users by investing in digital channels as a way to disseminate the multichannel communication strategy adapted. Bharwani and Mathews (2021) acknowledge the need for contactless guest interface and further highlight the use of technology tools to enhance guest experience and thus customers' satisfaction through personalization. However, how can hospitality companies measure the success of their digital communication strategy? The onus relies on HTT organizations that are able to use the available data in order to filter out the most valuable information based on customers' online fingerprints (Thomas & Chopra, 2019), in favor of brand optimization (Sakas et al., 2022b).

Global searches for "where to travel" have reached their highest level in 2022 (Google Trends, 2022). This fact demonstrates that there is a strong desire to travel and therefore online users are seeking for information pertaining their next trip. The evolution of social networking sites takes travel planning one step further, since online users tend to employ a social experience sharing behavior, which greatly impacts consumers' psychology and behavior (Kitsios et al., 2022).Yet, while the HTT ecosystem woks toward delivering strong user experience, there is still room for improvement (Godovykh & Tasci, 2020). Travel companies can leverage the behavioral data already at their disposal, along the end-to-end journey, with the use of modern digital systems that measure and predict consumer behavior (Mariani, 2020; Yallop & Seraphin, 2020).

Taking into consideration the psychological processes that online users undertake while searching online for travel experiences is fundamental for companies (Oliveira et al., 2020). Strategic communication is evolving as technologies are evolving. Without understanding customer decision-making process, all communication efforts will fall flat. Identifying customers' purchasing behavior is the future of eCommerce branding, profitability and growth (Mohseni et al., 2018). In this ever-changing landscape, travel organizations that give priority to user experience can gain brand loyalty and company resilience (Lee et al., 2018). This allows online users to perceive the brand as a trustful source and solidify a perceived value that will lead them to purchases. The employment of Big Data tools is crucial for strategic business goals, especially for customer journey improvement, since this analysis is closely associated with customer behavior and interactions (Buhalis & Volchek, 2021). Crucially, it can be used within the fields of both predictive and behavioral analytics, aiming at identifying key trends of behavioral patterns, in favor of brand optimization.

Multiple studies have been devoted in the HTT ecosystem based on big data analytics (Mariani, 2020; Yallop & Seraphin, 2020). The authors in one of the latest review papers clearly state that further attention need to be addressed on the HTT sector based on the data generated on social media platforms after severe virus outbreaks (Lv et al., 2022). To this end, the current paper focuses on users' behavioral attitude from 5.7 million Hubei province hospitality websites visitors, based on their online attitude as well as their reviews on Tripadvisor. The objective is to identify the impact of online user experience on their levels of satisfaction and provide fruitful information of how to develop an optimal communication strategy for the benefit of corporate branding.

Web analytics KPIs and hospitality websites visibility and ranking

Various previous researcheshave revealed that the extraction and analysis of web analytics are essential in order to improve corporate visibility and brand name (Saura, 2021). If properly processed and analyzed, big data can provide valuable insightsinto trends, behaviors and prospects so as companies to harness the best value from this investment. However, successfully converting these insights into actionable items greatly depends on implementing them on a real-time basis (Kushwaha et al., 2021). This is crucial for hospitality companies since the competition is huge and growing (Sakas et al., 2022a). Studying users' behavior on a website or social media is what is known as web analytics (Saura et al., 2017). In order to extract and analyze the Web analytics, a standardization process is needed (Saura et al., 2017). Hence, scholars perceive the Web analytics metrics as Key performance indicators (KPIs) (Chaffey & Patron, 2012; Kirsh & Joy, 2020; Fagan, 2014). KPIs can be defined as measurable metrics of performance over time for a certain goal (Chaffey & Patron, 2012). In this study, the behavioral KPIs are gathered from the web scrapping tools. Table 1, illustrates a detailed presentation of the behavioral KPIs.

Table 1
Web Analytics (WA) KPIs.

Key Performance Indicators	Description of the Key Performance Indicators
Organic Traffic	Users that visitthe corporate website through unpaid channels referred to as organic traffic (Baye et al., 2015).
Social Media Traffic	The WA KPI Social Traffic is generated when a visitor is forwarded from the corporate social media page to the hotel's website (Semrush, 2019).
Paid Traffic	This KPI refer to visitors that are landed on the hotel'swebsites through paid advertisement, for example, google ads (Blake et al., 2015; Semrush, 2019).
TripAdvisor Rating	This rate is referred to a visitor's total satisfaction level and is provided after the check-out process (Martin-Fuentes et al., 2018; Taecharungroj & Mathayomchan, 2019).
TripAdvisor Service Rate	This KPI is referred to the overall service satisfaction level reported by the customer after checking out and involves the hotel employees (Limberger et al., 2014)
TripAdvisor Value for Money Rate	This KPI is referred to the rating given by visitors regarding their perceptions on the balance between the hotel's service and paid rates(Soltani-Nejad et al., 2022). According to previous researchesthis is one of the main metrics of hospitality competitiveness (Cunningham et al., 2010).
Global Rank	This KPI is created by incorporating the websites' overall traffic (organic, social, and sponsored traffic) and behavioral metrics such as average time spent on site. The lower the rank, the more well-known the website is since a website ranked 2nd gets a better rating than a website ranked 12th (Sakas et al., 2022a; Vyas, 2019).
Average Time on Site	This metric is refered to the amount of time that a user spends on a website(Semrush, 2019).
Pages per Visit	The "Pages per Visits" WA KPI determines how many pages are viewed by users when they visit a hospitality website (Semrush, 2019).
User Engagement	This KPI is created by adding all behavioral web analytics (average time on site, pages per visits and total visits) (Drivas, Kouis, Kyriaki-Manessi, & Giannakopoulou, 2022; Sakas & Reklitis, 2021)
Total Visits	This WA KPI measures how many people visit a hotel website daily (Semrush, 2019).

Hypotheses development

Since the hospitality sector is one of the most competitive environments globally (Hossain et al., 2020), the examination of the industry through big data analytics provides tangible results for decision-makers, marketers and developers (Sakas et al., 2022a). By reviewing hospitality websites and customer satisfaction data and incorporating them into a larger marketing strategy to strengthen the firm's digital brand, decision-makers can optimize digital resources (Inanc–Demir & Kozak, 2019). Additionally, by adding those big data into their communication strategy, hospitality marketers can create competitive differentiation (Schuckert et al., 2015). The next hypotheses were created to investigate the effects of behavioral data extracted from hospitality websites and the effects of customer reviews on the digital brand name of the hospitality firms.

H1. The hospitality websites' "Organic Traffic" metric is affected by the total "Paid Traffic" metric and the websites' "Total Visits" metric.

The organic traffic metric is one of the most crucial web analytics and one of the main predictors of the digital brand name (Vyas, 2019). Therefore, it is crucial for a marketer to examine the effects of paid advertisement and the total number of users visited a website on the organic traffic metric.

H2. The website's "User Engagement" metric is affected by the "Average Time on Site" metric, the "Pages per Visits" metric and the website's "Organic traffic".

According to previous researches from the libraries to the logistics sector (Drivas, Kouis, Kyriaki-Manessi, & Giannakopoulou, 2022; Sakas & Reklitis, 2021), the behavioral metric of user engagement is an accurate estimator of the user activity on a corporate website. This hypothesis attempts to examine the effects of the behavioral web analytics pages per visit, average time on site and organic traffic on the user engagement metric.

H3. The total "Rating" metric is affected by the "User Engagement" metric, the "Service Rate" metric and the "Value for Money" Metric.

The authors attempt to examine the correlation of hospitality websites' activity on customer satisfaction. According to previous studies (Banerjee & Chua, 2016; Orea-Giner et al., 2022), TripAdvisor's customer satisfaction "Rating" metric is the main metric of customer satisfaction, and much effort has been given into how this metriccould be optimized. In this study, the focus has been placed on the effects of the hospitality websites' user engagement metric as well as the other two dominant (Cunningham et al., 2010; Zaman et al., 2016),) customer satisfaction metrics "Service Rate" and "Value for Money" rate on the total "Rating".

H4. The "Global Rank" metric is affected by the "Rating" metric, the "Service Rate" metric and the "Value for Money" Metric.

This hypothesis attempts to examine the effects of customer satisfaction analytics on hospitality websites' digital brand name. According to previous researches the main identifier of a website's digital brand name is the global rank metric (Labrecque et al., 2020; Mir-Bernal et al., 2017; Sakas et al., 2022a). The outcome can be valuable for marketers since has emerged as an unresponded riddle in the past years that has never been studied before via big data analysis. This question has been examined before with customers' verbal or written opinions and questionnaires (Azizan & Yusr, 2019; Khajeh Nobar & Rostamzadeh, 2018) but not on a basis of extracted behavioral big data. The extracted data can present the customer's pure activity by partially eliminating any possible cognitive bias (Merendino et al., 2018; Rao, et al., 2018).

Methodology

Data gathering and statistical analysis

An alternative research methodology has been implemented in this article in order to examine the effects of customers satisfaction metrics of Hubei province hospitality industry on the digital brand name. At first, behavioral analytics were gathered from 5.7 million users in5 hospitality websites for a period of 180 days, a sample which demonstrates customers' activity and ratings that have been gathered from 189 hotels in Hubei province. This methodology has been selected since the authors attempt to identify the behavioral cause-and-effect relationships between website activity and ratings by suppressing any possible cognitive bias (Rao et al., 2018; Merendino et al., 2018).The website behavioral data has been gathered from Semrush.com and the TripAdvisor ratings have been extracted from the web scraping tool named Octoparse.com. Behavioral metrics that have been gathered from Semrush include: "Bounce Rate", "Social Traffic", "Average Time on Site", "Global Rank", "Pages per Visit", "Paid Traffic", "Organic Traffic", and "Total Visitors". The data extracted from Octoparse include TripAdvisor's "Rating", "Service Rate" and "Value for Money Rate". The web scraping tools adopted in this research are presented with the intention to be examined on future studies by other researchers. The main prerequisite of the extraction is based on the full record of data. For instance, the reviews of all 189 hotels satisfy all customers' metrics (Rating, Service Rate, and Value for Money rate). That was crucial in order to proceed to the statistical analysis. The statistical analysis includes descriptive statistics, Pearson correlations between the examined metrics, and regression analysis. The authors seek to focus on their research approach in order to incorporate better objectivity in the outcome through rigor in the process (Kar & Dwivedi, 2020; Kar et al., 2023; Miranda et al., 2022; Singh et al., 2022).

Agent based model

The aim of a microscale ABM is to seek explanatory knowledge into the group behavior of agents following predefined guidelines (Giabbanelli et al., 2017).The agent-based models have been widely used in a big variety of disciplines, such as in crisis management in order to simulate civilian behavior in a crisis (Hoertel et al., 2020; Silva et al., 2020). According to previous researches, predictive ABMs are useful for marketing managers since they can reproduce and mimic customers' activity on a website(Bell & Mgbemena, 2017). This is crucial for marketers since they can explore and identify the root cause of consumer behavior and create adaptive digital communication strategies without investing funds in other costly technics such as marketing focus groups (Bell & Mgbemena, 2017; Rand & Rust, 2011; Sakas et al., 2022a).

Results

Statistical analysis

Table 2 presents the descriptive statistics of the study. The metrics are based on the data extracted from Semrush, and TripAdvisor. In order to better display the overall findings for the hospitality industry, the obtained data were combined by category.

Table 3 highlights the significant Pearson's correlations between the examined metrics. More specifically, positive correlations were found between organic traffic, paid traffic, and total visits with $\rho = 0.728**$ and $\rho = 0.909**$ respectively. Additionally, a significant positive correlation has been found between total visits and paid traffic with $\rho = 0.814**$. This finding highlights the importance of paid advertisements in search engines and their positive effect on the website's traffic and visibility. The first hypothesis' regression analysis is presented in Table 4. P-values less than 0.05 can determine the model's significance. This significant regression with $R2$=0.827 indicates that for every 1%

Table 2
Descriptive Statistics for 180 days.

	Mean	Min	Max	Std. Deviation
Organic Traffic	21,168,106.44	2304,851.00	51,121,311.00	14,138,967.18
Social Traffic	82,743.23	1458.00	232,244.00	64,864.51
Paid Traffic	763,330.70	29,167.00	3117,139.00	788,476.85
TripAdvisor Rating	39.70	25.00	50.00	4.97
TripAdvisor Service Rate	39.25	20.00	50.00	5.35
TripAdvisor Value for Money Rate	38.65	25.00	50.00	5.12
Global Rank	24,814.77	787.00	84,408.00	31,917.69
Average Time on Site	449.32	228.00	623.00	104.12
Pages per Visit	3.38	2.135883	4.327859	0.69
User Engagement	13,409,233.57	827,523.00	33,327,199.00	8485,329.73
Total Visits	22,997,296.42	1293,200.00	57,915,806.00	15,162,202.80

Table 3
Pearson's Correlations for the first hypothesis.

	Organic Traffic	Paid Traffic	Total Visits
Organic Traffic	1		
Paid Traffic	0.728**	1	
Total Visits	0.909**	0.814**	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 4
Regression analysis for the first hypothesis.

Variables	*Standardized Coefficient*	R^2	*F*	*p Value*
*Constant (*Organic Traffic*)*	–	0.827	76.334	<0.001
Paid Traffic	−0.034			.789
Total Visits	0.937			<0.001

rise in organic traffic an increase can be observed in total visits by 93.7% and a decrease in paid traffic by 3.4%.

Table 5 highlights the significant Pearson's correlations between the metrics. More precisely, positive correlations have been identified between the user engagement metric and the average time on site metric with ρ=0.760, the pages per visits metric with $\rho = 0.760$ $**$, the pages per visits metric with $\rho = 0.423 **$ and the organic traffic metric with $\rho = 0.880 **$. Additionally, positive significant correlations have been found between average time on site and pages per visit with $\rho = 0.349 *$ and organic traffic with $\rho = 0.827 **$ respectively. Finally, a positive correlation can be observed between organic traffic and pages per visit with the $\rho = 0.413*$. This finding illustrates the crucial role of those parameters in user engagement. The second hypothesis' regression model is presented in Table 6.With $P<0.05$ the model is significant. This significant regression with $R^2 = 0.781$ indicates that for every 1% rise in user engagement an increase can be observed in pages per visit by 7.1%, an increase in average time on site by 10% and an increase in organic traffic by 76.7%.

Table 7 highlights the significant Pearson's correlations between the parameters. More specifically, positive significant correlations were found between total "Rating" and the user engagement with $\rho = 0.624$ $**$, the service rate with $\rho = 0.665 **$ and the value for money rate with $\rho = 0.569 **$. Additionally, non-significant correlations have been found between user engagement and the service rate with $\rho = 0.218$ and the value for money rate with $\rho = -0.002$. The main interesting outcome of this hypothesis relies on the fact that user engagement highly affects the total "Ranking" metric but not the service rate and the value for money metric while "Rating" is highly affected by all metrics. Finally, the significant regression presented in Table 8, with $R^2 = 0.423$ indicates that for every 1% rise in Rating an increase can be observed in user engagement by 57.4%, in service rate by 23.5%, and a decrease in value for money rate by 4%.

Table 9 illustrates the Pearson's correlations between the examined metrics. More specifically, non-significant negative correlations were found between the total "Rating" and the global rank with $\rho = -0.233$. This is beneficial for global ranking since ranking in place 150 is worse than a global ranking in place 3. Consequently, when the global rank is getting lower values, it means that the website is going higher in ranking. Additionally, negative significant correlationshave been observed between global rank and the total visits $\rho = -0.471 **$, the social media traffic metric with $\rho = -0.415*$ and the paid traffic metric

Table 5
Pearson's Correlations for the second hypothesis.

	User Engagement	Average Time on Site	Pages per Visits	Organic Traffic
User Engagement	1			
Average Time on Site	0.760**	1		
Pages per Visits	0.423*	0.349*	1	
Organic Traffic	0.880**	0.827**	0.413*	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 6
Regression analysis for the second hypothesis.

Variables	*Standardized Coefficient*	R^2	*F*	*p Value*
*Constant (*User Engagement*)*	–	0.781	36.866	<0.001
Average Time on Site	0.100			.507
Pages per Visits	0.071			.448
Organic Traffic	0.767			<0.001

Table 7
Pearson's Correlations for the third hypothesis.

	Rating	User Engagement	Service Rate	Value for Money Rate
Rating	1			
User Engagement	0.624**	1		
Service Rate	0.665**	0.218	1	
Value for Money Rate	0.569**	−0.002	0.535**	1

** Correlation is significant at the 0.05 level (2-tailed).

Table 8
Regression analysis for the third hypothesis.

Variables	*Standardized Coefficient*	R^2	*F*	*p Value*
*Constant (*Rating*)*	–	0.423	7.561	<0.001
User Engagement	0.574			<0.001
Service Rate	0.235			.195
Value for Money Rate	−0.004			.471

Table 9
Pearson's Correlations for the fourth hypothesis.

	Global Rank	Rating	Total Visits	Social Media Traffic	Paid Traffic
Global Rank	1				
Rating	−0.233	1			
Total Visits	−0.471**	0.651**	1		
Social Media Traffic	−0.415*	0.707**	0.836**	1	
Paid Traffic	−0.567**	0.645**	0.926**	0.816**	1

[*] Correlation is significant at the 0.05 level (2-tailed).

with $\rho = -0.567**$. All the above correlations indicate a beneficial impact on the corporate digital brand name through global ranking. A second observation can be located in the "Rating metric" in correlation to the paid traffic from search engines with $\rho = 0.645**$ and the traffic from corporate social media with $\rho = 0.707**$. It seems that is beneficial for hospitality companies to invest both in social media and in search engine advertisements in order to improve customer satisfaction. Furthermore, positive significant correlations can be observed between the number of total visitors with the social media traffic ($\rho = 0.836**$) and with the paid traffic ($\rho = 0.926**$). Finally, the regression presented in Table 10reveals that for every 1% rise in global rank, an increase can be observed in total "Rating" by 21,4%, and a decrease in total visits by 5.3%, in social media traffic by 28.2%, and paid traffic by 39,6%.

Agent based simulation model

In order to create the ABM the Anylogic software 8.7.12 has been used and programmed with the assistance of the "Java" programming language. To give a micro-scale examination of the problem, an ABM was used (Giabbanelli et al., 2017). Since it simulates real-world scenarios and analyzes user behavior to derive practical digital marketing approaches, its deployment is advantageous for businesses in order to optimize their marketing strategies (Rand & Rust, 2011).Furthermore, by utilizing ABMs, businesses are able to fully understand the benefits that big data offers in terms of how users interact with their webpage and social media platforms and their potential for expansion (Negahban & Yilmaz, 2014; Rand & Rust, 2011).Predictive modeling is used to capture tourists' sentiments, as they emerge from their online interaction on social networking platforms, and goes beyond the static users' behavioral knowledge to the dynamic comprehension of their expectations and perceptions (Agrawal et al., 2022). The model represents the typical actions of a visitor to a tourism and hospitality website. The white top box, in particular, shows the starting position of an agent. The model mimics every step of the procedure, from the customer's website visit via paid, organic, or social media traffic to the Improvement of the global rank (brand-name). Variables (V) towards the bottom of the figure in Fig. 1 represent the potential responses to the necessary changes. As a result, the agents begin to move, and the ABM shows this movement as black arrows. The Poisson distribution was chosen for this model because it allows the statistical analysis shown in Section 4.1 to be incorporated into the model (Giabbanelli et al., 2017; Hoertel et al., 2020).

The simulation begins from the top white box, where a potential visitor is distributed between the paid traffic, the social traffic, and the organic traffic. Those traffics present the main sources of a corporate website. For instance, the customer can visit the website through google or social media advertising or by typing directly the company's url due to his familiarity with the brand. The traffic is illustrated with yellow boxes, despite the fact that potential visitors may choose to stay or abandon the website. The white box and the metric bounce rate Illustrate their intention to leave the website after viewed only a single page. When a user visits a website, two main categories are being produced: the rating category (green boxes) and the user engagement category (purple boxes). Finally, the user engagement of the corporate website and the TripAdvisor rating produce the corporate websites' global ranking (Brand name).

The outcomes of the population allocation over a 6 month period are shown in Figs. 2a and 2b. Fig. 3a depicts the ninth day of the simulation, with the gray agents are the potential tourists and the yellow agents for the webpages' traffic coming from social, paid, or organic sources. The simulation is shown in Fig. 3b at the end of the 89th day, and it shows that more purple agents, which represent the user engagementvariables, are formed, along with more blue agents, which representthe the global rank. This is to be expected as blue agents, who stand in for the global rank, start to appear after 70 days. This outcome could be predicted since brand name is being established after the 70th day.The cyan agents also represent the rating variables.

The time chart in Fig. 3, illustrates the progression of the contribution of the examined metrics based on the correlation analysis and the regression analysis. While the user engagement parameter, which is rather erratic, can be observed in a spike in the global ranking on day 5, from the moment that the advertisement is displayed and specifically on the 20th day, there is a spike on the ratings. There is also, a negative spike on the date 92 for both global ranking and ratings and this is A fact that can be justified due to the seasonality of the HTT sector of the seasonality of the tourism sector. An interesting outcome is that an increase in global ranking and ratings is observed after the 120th day. However, from the 170th day and beyond, there is a greater increase in both variables due to the fact that the company's brand name has already been established. This outcome fully aligns with previous researches into HTT websites (Sakas et al., 2022a), however it comes in contrast with previous studies on different sectors, such as logistics, healthcare, and libraries (Corritore et al., 2012; Drivas, Kouis, Kyriaki-Manessi, & Giannakopoulou, 2022; Sakas et al., 2022a) and clothing industry (Goldsmith & Flynn, 2004).

Table 10
Regression analysis for the fourth hypothesis.

Variables	*Standardized Coefficient*	R^2	*F*	*p Value*
Constant (Global Rank)	–	0.288	3.029	.033
Rating	0.214			0.343
Total Visits	−0.053			0.894
Social Media Traffic	−0.282			0.380
Paid Traffic	−0.396			0.159

Discussions

The major objectives of this study are to explore how users' online behavioral attitudes that affect the visibility of TripAdvisor's rating and the digital development of the tourism websites' brand as well as to offer concrete guidelines on communication optimization strategies with the intention to strengthen corporate branding. More specifically, the first hypothesis (H1) is accepted and it is in full alignment with previous researches (Baye et al., 2015; Sakas & Reklitis, 2021; Simonov et al., 2018). The paid traffic has beneficial effects on the improvement of the total traffic in tourism websites. The second hypothesis (H2) is also accepted. This interesting finding is important for the HTT sector since it verifies the outcomes of previous studies within the same industry, however it does not confirm the outcomes of previous researches in different sector, such as the logistics, healthcare, and libraries (Corritore et al., 2012; Drivas, Kouis, Kyriaki-Manessi, & Giannakopoulou, 2022; Sakas et al., 2022a). Customers in the logistics, health care, and libraries sector prefer to use parcel tracking, or doctor tracking information, or a book title search without any distractions and leave the website as soon as possible. In the case of the hospitality industry developers needs incorporate into their websites more engaging content including photos, mini-games, and live simulation of the living area in order to optimize engagement (Ali, 2016; Lu & Stepchenkova, 2014; Xu & Schrier, 2019).

This third hypothesis (H3) is accepted, and it is in full alignment with

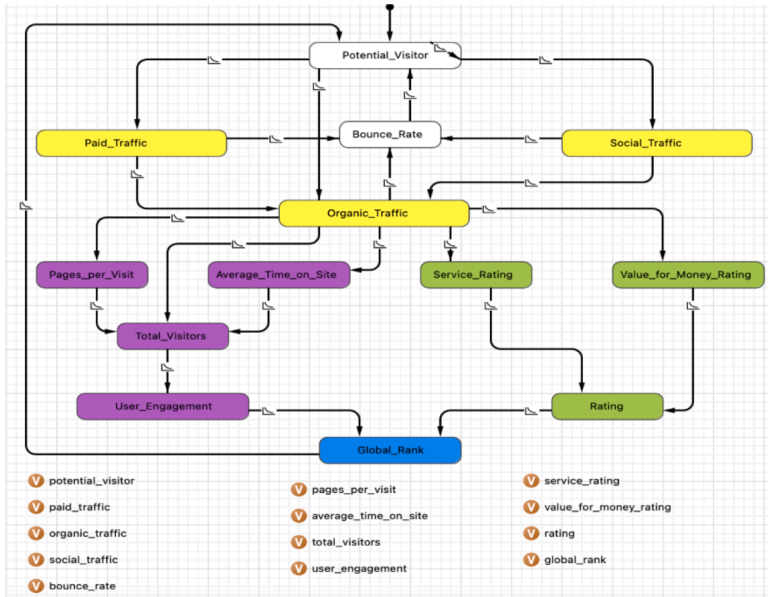
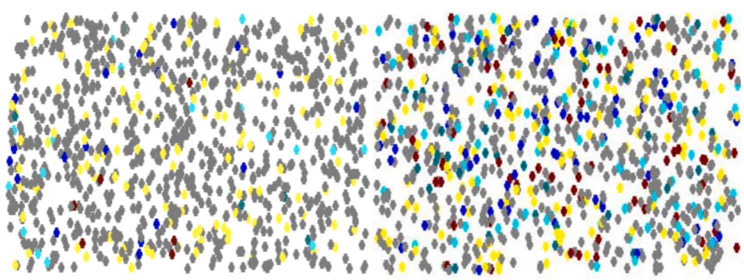


Fig. 1. Agent based model.



(a) (b)

Fig. 2. (a). The distribution of the population in a 180-day simulation using 10,000 agents. Day 9. Fig. 2(b). The distribution of the population in a 180-day simulation using 10,000 agents. Day 89.

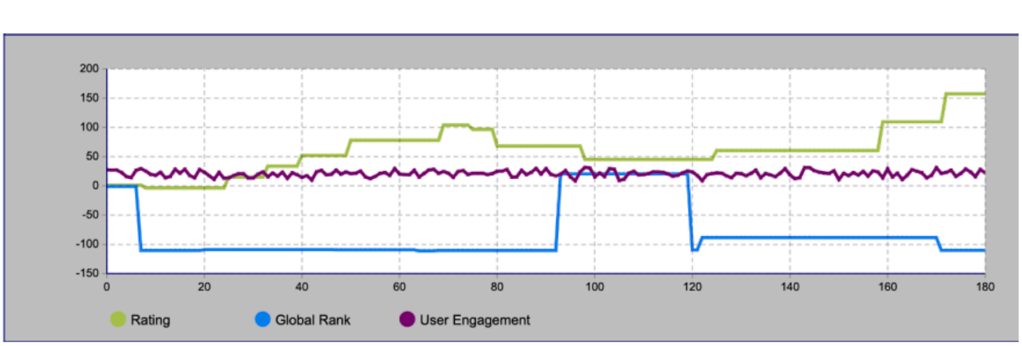


Fig. 3. The timeline shows the progression of the contribution of the TripAdvisor Rating, the Global Ranking and the User Engagement.

previous researches in hotels and museums (Fernández-Hernández et al., 2020; Han & Anderson, 2022). More specifically, the TripAdvisor's Rating is highly affected by the customer activity of the tourism website as well as from other rating metrics such as service rate and value for money rate. Fig. 4

The final hypothesis (H4) is also accepted and aligns with previous researches (Labrecque et al., 2020; Mir-Bernal et al., 2017; Sakas et al., 2022a), but generalizations must be made carefully as R2 (0.288) is rather constrained. This finding suggests to marketeers that in order to improve the digital brand name needs to invest more in social media advertisements and google advertisements. The findings of the current study were successfully put into action with the development of theAMB model, indicating that the improvement of the corporate brand name is achieved through the development of websites with more engaging content. Finally, in order to optimize organic traffic and lead generation to the tourism websites, marketers need to widen the pool which will lead to a better conversion rate and geometrically improve customer retention rate.

Theoretical implications

The present study clearly demonstrates the user engagement metrics

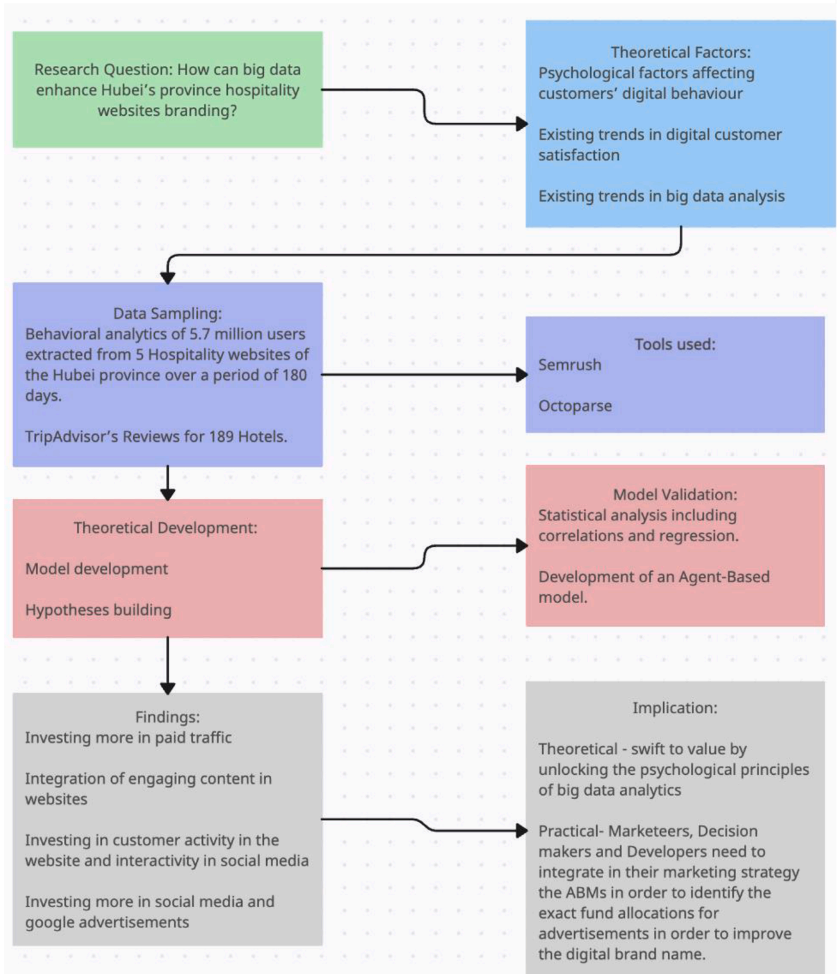


Fig. 4. Conceptual model that illustrates the visualization and validity of the research.

that impact consumers' online behavior during online shopping, on the post-COVID-19 era in the context of HTT organizations. This outcome co-aligns with Sajid et al., and Haider (2022) study in which the shift toward digital services is well-established. The purchasing behavior of users is constantly changing, not only due to the explosion of technology that Industry 5.0 offers, but also due to unforeseen circumstances that could not be predicted 3 years ago (Terzić et al., 2022). This online digital growth and penetration is expected to persist after the pandemic is over (Jiang, 2020).

Rather than striving to automate absolutely everything in the HTT ecosystem (Ivanov, 2020), the current research suggests that there should be a shift to value. Given the importance of psychology behavioral principles, analyzed in the literature review, the balance between customers' expectations and perceived users' experience will be met if providing online customers with fewer opportunities to explore thus minimize information overload so as to simplify processes and steer users along a better journey. For example, websites should provide fruitful content to maintain customers for a longer period of time on-site, however, this content has to rely on minimalist guidelines and be based on authentic users generated content (UGC). Travel planning is greatly affected by UGC (Mendes-Filho et al., 2018) since it cultivates corporate trust and brand empowerment (Bakshi et al., 2021), leading to increased conversion rates and positive e-Word-of-mouth communication (Kim & Jonshon, 2016). As travel reviews are perceived as a validating factor for travel inspiration (Siegel & Wang, 2019), UGC is considered as an empowerment factor that motivates travel experiences (Sakas et al., 2022a).

Recent advances in data-driven decision-making analytics focus on ensuring companies sustainability (Suha & Sanam, 2023), which reflects their link to optimize process and drive business growth (Unhelkar et al., 2022).As the HTT industry move towards greater sustainability, considering psychology principles could successfully contribute to the development of an effective corporate brand communication strategy. The new challenge for the industry is to take psychology out of the lab and into the hospitality field, by unlocking the dynamics of big data analytics. Thanks to the vast opportunities the online world provides, big data offers HTT companies a behind-the-scenes view into their customers perceptions and sentiments (Mehraliyev et al., 2022). The tough task for companies is to link up satisfaction across all touchpoints and have clear indications of the levels of customers satisfaction across the overall customer journey. In essence, the challenge is to master the digital journey.

To sum up, measuring the travel experience is hard to make. With the use of big data analytics, the HTT sector can measure trends and predict behaviors (Mariani & Baggio, 2022). However, solely relying on the behavioral attitude of websites users is no longer enough for digital brand optimization. For perception scales to deliver fruitful information, deeper analysis is required on the factors that affect the online buying behavior. The authors of the current study suggest deeper analysis on reviews and ratings in order to overcome implicit data and collected reliably emotions or senses. Since sensing customer feedback throughout the entire journey is one of the most important indications of corporate performance (Kim et al., 2020),the shift to value, which hospitality companies need in order to achieve a competitive advantage and higher levels of customers' satisfaction, is also found on the personalization of online services, as the basis of a multichannel communication strategy (Sakas et al., 2022a), by further adding the human input (Mourtzis et al., 2022).

Understanding the value and contribution of different psychological principles that influence human behavior during their customer journey is of paramount importance for HTT organizations. Travelers are willing to adopt new patterns of behavior when high-risks are associated, which highlights the interconnection between customers' overall risk perception and their decision-making process conformation (Terzić et al., 2022). Therefore, as tourists attempt to bridge the zone of tolerance between their expectations and the actual perceived experience during crisis situations (Chen, 2014;), they are motivated to search for more information regarding travel-related decisions, formulating a new information-seeking process (Meng et al., 2021).

While psychology principles gain the attraction of businesses for the reason that they study a variety of perspectives on customers' reciprocation on information searching, purchasing behavior and brand selection (Ozuem et al., 2021), there is still room for improvement by taking advantage of the vast opportunities the online world provides so as to build a bridge between consumer online behavior and customer journey (Buhalis & Volchek, 2021). When customers search online from the need to the purchase phase, they create unconsciously behavioral data as an aftermath of their attitude in a service eco-system (Boone et al., 2019). Interesting marketing opportunities can be found at the intersection of behavioral psychology and customer-experience journey. The more a company digs into consumer psychology, the more opportunities will be revealed so as to achieve higher conversion rates and strengthen the current relationships. Capitalizing on the availability of data from diverse sources, for example both websites and social media platforms, should be seen as a pivotal strategic imperative to uncover behavioral patterns and make predictions.

Practical implications

The authors of the current study provide several guidelines to specific target groups on how to overcome information overload and put into action the communication practices suggested. It is evident that mapping the travel customer journey can help HTT companies to understand how consumers go through the sales funnel, so as to employ the suitable actions that would improve customers' overall experience (Reklitis et al., 2017). As we live in the era of personalization (Sakas et al., 2022a), customers demand special attention that could only be delivered if walking in their shoes. For example, forcing customers to buy on the early stage of their journey will definitely lead to increased bounce rates.Rather, adopting a hyper-personalization marketing strategy, empowered by big data insights, throughout the early stage of the digital customer journey,goes further than traditional segmentation and builds a competitive advantage (Saheb et al., 2021; Sharma, Kumar & Chuah, 2021). Companies should evaluate the behavioral psychology principles throughout the entire customer journey in an attempt to avoid such failures and to deliver high users' experiences.

a) Website developers: The first and fundamental aspect for website developers is to understand design psychology so as to improve user experience (Kuehnl et al., 2019). By taking into consideration psychological principles such as Hick's Law, Miller's Law and Von-Restorff Effect, will inevitably contribute to the development of websites that offer seamless experiences, increase customers' engagement and boost their interaction, satisfaction and ultimately conversion rates. For example, hospitality websites with more engaging content, with 3D animations, would attract the attention of users. However, in order to avoid information overload, they should narrow down the options offered to users precisely to those they need so as to accomplish their goal, for instance via personalized recommendation applications (Sharma, Rana & Kumar, 2021).
b) Marketers: The outcomes of the current study culminate with a set of four critical actions for marketers so as to understand the digital customer journey and develop an effective brand communication strategy. First, during the "dreaming" stage, the company's goal is to generate human-level connection, though content marketing (Lopes et al., 2022). The analysis of big data will make travel companies understand their customers as microsegments, and thus help them create the relevant engaging content, though blogs and websites, so as to grab the attention of their personas. Second, as the customer enters the "researching" stage, HTT companies have all the data they need to acknowledge customers' wants, needs, feelings, actions and aspirations, by studying users' engagement metrics from both websites and social media platforms. Therefore, companies could design thoughtful customer-experience interventions by asking for customers' engagement (Liu et al., 2021). For example, ask them to download "how-to" guides, provide them with testimonials or inspiring photos and videos of the services on offer. Third, during the "booking" and "pre-travel" phase, customers' need to feel safe with their choice and therefore, marketers should keep them engaged with emails and newsletters that will contribute to the enjoyment of their upcoming trip. Last, during the "post-travel" phase, marketers should encourage customers to express their feelings by testifying their opinion, sharing photos on social media, and tagging the brand since this action will make them feel valuable and part of a brand community (Touni et al., 2020). For example, HTT companies should give their clients more opportunities for discussion, collaboration, and engagement through social media platforms. This is an excellent opportunity for companies to track the online behavior of existing and new users and datafy users' online behavior so as to acknowledge trends and identify potential failure points in their brand communication strategy.
c) Decision makers: The present study suggests to decision makers to employ customer journey mapping as they provide visualizations of the variables that greatly affect the behavior of online users (Umesh & Kagan, 2015). With the employment of ABM model, they will be able to understand the cause-and-effect connections between the user engagement metrics, identify their impact on users experience and take the appropriate decisions so as to lead customers through the sales funnel.

Research limitations and future recommendations

The main focus of this paper is to acknowledge the importance of using big data analytics on users' online behavior on both hospitality websites and reviews, in an attempt to predict trends and to offer concrete guidelines so as to develop a solid brand communication strategy. However, the findings of this study must be seen in the light of some limitations. First, although the sample of the current study is big enough to provide fruitful information on users' online behavior, it has geographical limitations. Data from of Hubei provincehospitality websites has been gathered and analyzed, leaving room for future studies to investigate the same parameters on a larger scale.

In addition, while data from Tripadvisor's reviews has been collected and evaluated in an attempt to collect sentiments, it would be of much research interest to employ a qualitative analysis so as to determine the variables that affect customers' online behavior before, during and after the sale by using perceptions scales.

Last, since customers' motivations, preferences, and decisions are able to affect the development of brand communication strategies, more insights into neuromarketing would elucidate the physiological and neural signals of customers and open new avenues into online customers' behavior.

Conclusions

The purpose of the current paper is to provide evidence on the impact of customers' online behavior on corporate digital branding and offer guidelines on how companies could optimize customers' satisfaction by leveraging the dynamic of big data analytics. Gathering and analyzing the digital behavior and journey of million users can provide fruitful information and valid insights on businesses within the HTT sector as the literature suggests (Buhalis & Volchek, 2021; Lv et al., 2022). However, there is little empirical evidence on how marketing managers could benefit from the information overload (Saxena & Lamest, 2018). The authors of the present research attempt to analyze the data collected from 189 hotels and 5,7 million visitors, generated from websites and social platforms, and interpret the results into actual guidelines so as to develop an effective brand communication strategy.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Agrawal, R., Wankhede, V. A., Kumar, A., Luthra, S., & Huisingh, D. (2022). Big data analytics and sustainable tourism: A comprehensive review and network based analysis for potential future research. *International Journal of Information Management Data Insights, 2*(2), Article 100122.

Ali, F. (2016). Hotel website quality, perceived flow, customer satisfaction and purchase intention. *Journal of Hospitality and Tourism Technology, 7*(2), 213–228. https://doi.org/10.1108/jhtt-02-2016-0010

Ansar, W., & Goswami, S. (2021). Combating the menace: A survey on characterization and detection of fake news from a data science perspective. *International Journal of Information Management Data Insights, 1*(2), Article 100052.

Azizan, N. S., & Yusr, M. M. (2019). The influence of customer satisfaction, Brand Trust, and brand image towards Customer Loyalty. *International Journal of Entrepreneurship and Management Practices, 2*(7), 93–108. https://doi.org/10.35631/ijemp.270010

Baharom, S. N., Anuar, S. B. M., Zolkifly, N. H., & Tahir, H. M. (2020). The people's behavior change during pandemic of COVID-19; The four aspects of design thinking. In *International Conference of Innovation in Media and Visual Design (IMDES 2020)* (pp. 180–186). Atlantis Press.

Banerjee, S., & Chua, A. Y. (2016). search of patterns among travellers' hotel ratings in TripAdvisor. *Tourism Management, 53*, 125–131. https://doi.org/10.1016/j.tourman.2015.09.020

Bauer, C., Spangenberg, K., Spangenberg, E. R., & Herrmann, Andreas (2022). Collect them all! Increasing product category cross-selling using the incompleteness effect. *J. of the Acad. Mark. Sci., 50*, 713–741. https://doi.org/10.1007/s11747-021-00835-6

Baye, M. R., De los Santos, B., & Wildenbeest, M. R. (2015). Search engine optimization: What drives organic traffic to retail sites? *Journal of Economics & Management Strategy, 25*(1), 6–31. https://doi.org/10.1111/jems.12141

Bell, D., & Mgbemena, C. (2017). Data-driven agent-based exploration of customer behavior. *Simulation, 94*(3), 195–212. https://doi.org/10.1177/0037549717743106

Bharwani, S., & Mathews, D. (2021). Post-pandemic pressures to pivot: Tech transformations in luxury hotels. *Worldwide Hospitality and Tourism Themes, 13*(5), 569–583. https://doi.org/10.1108/WHATT-05-2021-0072

Bakshi, S., Gupta, D. R., & Gupta, A. (2021). Online travel review posting intentions: A social exchange theory perspective. *Leisure/Loisir, 45*(4), 603–633. https://doi.org/10.1080/14927713.2021.1924076

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. *Econometrica : Journal of the Econometric Society, 83*(1), 155–174. https://doi.org/10.3982/ecta12423

Bonfanti, A., Vigolo, V., & Yfantidou, G. (2021). The impact of the Covid-19 pandemic on customer experience design: The hotel managers' perspective. *International Journal of Hospitality Management, 94*, Article 102871. https://doi.org/10.1016/j.ijhm.2021.102871

Boone, T., Ganeshan, R., Jain, A., & Sanders, N. R. (2019). Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting, 35*(1), 170–180. https://doi.org/10.1016/j.ijforecast.2018.09.003

Bozkurt, S., Gligor, D., & Gligor, N. (2022). Investigating the impact of psychological customer engagement on customer engagement behaviors: The moderating role of customer commitment. *Journal of Marketing Analysis, 10*, 408–424. https://doi.org/10.1057/s41270-021-00146-3

Buhalis, D., & Volchek, K. (2021). Bridging marketing theory and big data analytics: The taxonomy of marketing attribution. *International Journal of Information Management, 56*, Article 102253. https://doi.org/10.1016/j.ijinfomgt.2020.102253

Chaffey, D., & Patron, M. (2012). From web analytics to digital marketing optimization: Increasing the commercial value of digital analytics. *Journal of Direct, Data and Digital Marketing Practice, 14*(1), 30–45. https://doi.org/10.1057/dddmp.2012.20

Chatterjee, S. (2020). Drivers of helpfulness of online hotel reviews: A sentiment and emotion mining approach. *International Journal of Hospitality Management, 85*. https://doi.org/10.1016/j.ijhm.2019.102356

Chen, K. Y. (2014). Improving importance-performance analysis: The role of the zone of tolerance and competitor performance. The case of Taiwan's hot spring hotels. *Tourism Management, 40*, 260–272. https://doi.org/10.1016/j.tourman.2013.06.009

Corritore, C. L., Susan, W., Beverly, K., & Robert, P. M. (2012). Online trust and health information websites. *International Journal of Technology and Human Interaction, 8*(4), 92–115. https://doi.org/10.4018/jthi.2012100106. Available at:.

Cunningham, Pádraig, Smyth, Barry, Wu, Guangyu, & Greene, Derek (2010). "Does TripAdvisor Makes Hotels Better?," December. https://researchrepository.ucd.ie/handle/10197/12386.

Drivas, I. C., Kouis, D., Kyriaki-Manessi, D., & Giannakopoulou, F. (2022). Social media analytics and metrics for improving users engagement. *Knowledge* (pp. 225–242). https://doi.org/10.3390/knowledge2020014. MDPI AG, Jg. 2, Nr. 2, S.

Fagan, Jody Condit (2014). The Suitability of Web Analytics Key Performance Indicators in the Academic Library Environment. *The Journal of Academic Librarianship, 40*(1), 25–34.

Fernández-Hernández, R., Vacas-Guerrero, T., & García-Muiña, F. E. (2020). Online reputation and user engagement as strategic resources of Museums. *Museum Management and Curatorship, 36*(6), 553–568. https://doi.org/10.1080/09647775.2020.1803114

Gagan, D. S., Asha, T., & Justin, P. (2021). Reviving tourism industry post-COVID-19: A resilience-based framework. *Tourism Management Perspectives, 37*, Article 100786. https://doi.org/10.1016/j.tmp.2020.100786

Giabbanelli, P. J., Gray, S. A., & Aminpour, P. (2017). Combining fuzzy cognitive maps with agent-based modeling: Frameworks and pitfalls of a powerful hybrid modeling approach to understand human-environment interactions. *Environmental Modelling and Software, 95*, 320–325. https://doi.org/10.1016/j.envsoft.2017.06.040

Godovykh, M., & Tasci, A. D. A. (2020). Customer experience in tourism: A review of definitions, components, and measurements. *Tourism Management Perspectives, 35*, Article 100694. https://doi.org/10.1016/j.tmp.2020.100694

Goldsmith, R. E., & Flynn, L. R. (2004). Psychological and behavioral drivers of online clothing purchase. *Journal of Fashion Marketing and Management: An International Journal, 8*(1), 84–95. https://doi.org/10.1108/13612020410518718

Google Trends (2022). Retrieved from https://trends.google.com/trends/explore?date=today%205-y&q=where%20to%20travel.

Han, S., & Anderson, C. K. (2022). The dynamic customer engagement behaviors in the customer satisfaction survey. *Decision Support Systems, 154*, Article 113708. https://doi.org/10.1016/j.dss.2021.113708

Hoertel, N., Blachier, M., Blanco, C., Olfson, M., Massetti, M., & Rico, M. S. (2020). Author correction: A stochastic agent-based model of the SARS-COV-2 epidemic in France. *Nature Medicine, 26*(11). https://doi.org/10.1038/s41591-020-1129-4, 1801-1801.

Hossain, M. S., Kannan, S. N., & Raman Nair, S. K. (2020). Factors influencing sustainable competitive advantage in the hospitality industry. *Journal of Quality Assurance in Hospitality & Tourism, 22*(6), 679–710. https://doi.org/10.1080/1528008x.2020.1837049. Available at:.

Hu, L., & Olivieri, M. (2021). Social media management in the traveller's customer journey: An analysis of the hospitality sector. *Current Issues in Tourism, 24*(12), 1768–1779. https://doi.org/10.1080/13683500.2020.1819969

Hu, H., & Krishen, A. S. (2019). When is enough, enough? Investigating product reviews and information overload from a consumer empowerment perspective. *Journal of Business Research, 100*, 27–37. https://doi.org/10.1016/j.jbusres.2019.03.011

Inanc-Demir, M., & Kozak, M. (2019). 'Big data and its supporting elements: Implications for tourism and hospitality marketing'. In *Big Data and Innovation in Tourism, Travel, and Hospitality. Singapore: Springer Singapore, pp. 213–223.Kirsh, Ilan, and Mike Joy. 2020. "Splitting the Web Analytics Atom: From Page Metrics and KPIs to Sub-Page Metrics and KPIs." In Proceedings of the 10th International Conference on Web Intelligence, Mining and Semantics, 33–43. WIMS 2020*. New York, NY, USA: Association for Computing Machinery.

Ismaili, P. B. (2020). Digital marketing–a novel sequential approach using knowledge digraph contribution. *Journal of Business and Behavioral Sciences, 32*(1), 72–86. Retrieved from http://asbbs.org/files/2020/JBBS_32.1_Spring_2020.pdf#page=72.

Ivanov, S. (2020). The impact of automation on tourism and hospitality jobs. *Inf Technol Tourism, 22*, 205–215. https://doi.org/10.1007/s40558-020-00175-1

Jiang, X. (2020). Digital economy in the post-pandemic era. *Journal of Chinese Economic and Business Studies, 18*(4), 333–339. https://doi.org/10.1080/14765284.2020.1855066

Kar, A. K., & Dwivedi, Y. K. (2020). Theory building with big data-driven research – moving away from the "what" towards the "why". *International Journal of Information Management, 54*, Article 102205. https://doi.org/10.1016/j.ijinfomgt.2020.102205

Kar, A. K., Angelopoulos, S., & Rao, H. R. (2023). Guest editorial: Big Data-driven theory building: Philosophies, guiding principles, and common traps. *International Journal of Information Management, 71*, Article 102661. https://doi.org/10.1016/j.ijinfomgt.2023.102661

Khajeh Nobar, H. B., & Rostamzadeh, R. (2018). The impact of customer satisfaction, customer experience and customer loyalty on Brand Power: Empirical Evidence from Hotel Industry. *Journal of Business Economics and Management, 19*(2), 417–430. https://doi.org/10.3846/jbem.2018.5678

Kandampully, J., & Solnet, D. (2020). Competitive advantage through service in hospitality and tourism: A perspective article. *Tourism Review, 75*(1), 247–251. https://doi.org/10.1108/TR-05-2019-0175

Kim, A. J., & Johnson, K. K. P. (2016). Power of consumers using social media: Examining the influences of brand-related user-generated content on Facebook.

Computers in Human Behavior, 58, 98–108. https://doi.org/10.1016/j.chb.2015.12.047
Kim, M., Yin, X., & Lee, G. (2020). The effect of CSR on corporate image, customer citizenship behaviors, and customers' long-term relationship orientation. *International Journal of Hospitality Management, 88*. https://doi.org/10.1016/j.ijhm.2020.102520
Kitsios, F., Mitsopoulou, E., Moustaka, E., & Kamariotou, M. (2022). User-Generated Content behavior and digital tourism services: A SEM-neural network model for information trust in social networking sites. *International Journal of Information Management Data Insights, 2*(1), Article 100056.
Kuehnl, C., Jozic, D., & Homburg, C. (2019). Effective customer journey design: Consumers' conception, measurement, and consequences. *Journal of the Academic Marketing Science, 47*, 551–568. https://doi.org/10.1007/s11747-018-00625-7
Kushwaha, A. K., Kar, A. K., & Dwivedi, Y. K. (2021). Applications of big data in emerging management disciplines: A literature review using text mining. *International Journal of Information Management Data Insights, 1*(2), Article 100017.
Labrecque, L. I., Swani, K., & Stephen, A. T. (2020). The impact of pronoun choices on consumer engagement actions: Exploring top global brands' social media communications. *Psychology & Marketing, 37*(6), 796–814. https://doi.org/10.1002/mar.21341
Lee, H. J., Lee, K. H., & Choi, J. (2018). A structural model for unity of experience: connecting user experience, customer experience, and brand experience. *Journal of Usability Studies, 11*(1). Retrieved from https://uxpajournal.org/wp-content/uploads/sites/7/pdf/JUS_Lee_Nov2018.pdf.
Limberger, Pablo Flôres, Anjos, Francisco Antonio Dos, de Souza Meira, Jéssica Vieira, & Anjos, Sara Joana Gadotti dos (2014). Satisfaction in hospitality on TripAdvisor. Com: An analysis of the correlation between evaluation criteria and overall satisfaction. *Tourism & Management Studies, 10*(1), 59–65.
Liu, X., Shin, H., & Burns, A. C. (2021). Examining the impact of luxury brand's social media marketing on customer engagement: Using big data analytics and natural language processing. *Journal of Business Research, 125*, 815–826. https://doi.org/10.1016/j.jbusres.2019.04.042
Lopes, A. R., Porto, I. P. A. M., & Casais, B. (2022). Digital Content Marketing: Conceptual Review and Recommendations for Practitioners. *Academy of Strategic Management Journal, 21*(2), 1–17. Retrieved from https://www.researchgate.net/profile/Beatriz-Casais/publication/357746605_Digital_Content_Marketing_Conceptual_Review_and_Recommendations_for_Practitioners/links/61dd81d7034dda1b9eeda0be/Digital-Content-Marketing-Conceptual-Review-and-Recommendations-for-Practitioners.pdf.
Lu, W., & Stepchenkova, S. (2014). User-generated content as a research mode in tourism and hospitality applications: Topics, methods, and software. *Journal of Hospitality Marketing & Management, 24*(2), 119–154. https://doi.org/10.1080/19368623.2014.907758
Lv, H., Shi, S., & Gursoy, D. (2022). A look back and a leap forward: A review and synthesis of big data and artificial intelligence literature in hospitality and tourism. *Journal of Hospitality Marketing & Management, 31*(2), 145–175. https://doi.org/10.1080/19368623.2021.1937434
Magnini, V. P., & Dallinger, I. (2018). Consumer Information Overload and the Need to Prompt Script Deviations. *Journal of Quality Assurance in Hospitality & Tourism, 19*(3), 285–297. https://doi.org/10.1080/1528008X.2016.1230038
Mahdikhani, M. (2022). Predicting the popularity of tweets by analyzing public opinion and emotions in different stages of COVID-19 pandemic. *International Journal of Information Management Data Insights, 2*(1), Article 100053.
Mariani, M. (2020). Big Data and analytics in tourism and hospitality: A perspective article. *Tourism Review, 75*(1), 299–303. https://doi.org/10.1108/TR-06-2019-0259
Mariani, M., & Baggio, R. (2022). Big data and analytics in hospitality and tourism: A systematic literature review. *International Journal of Contemporary Hospitality Management, 34*(1), 231–278. https://doi.org/10.1108/IJCHM-03-2021-0301
Marques Santos, A., Madrid, C., Haegeman, K., & Rainoldi, A. (2020). Behavioural changes in tourism in times of COVID-19. *JRC121262, 22*(3), 121–147. Retrieved from https://publications.jrc.ec.europa.eu/repository/handle/JRC121262.
Martin-Fuentes, E., Mateu, C., & Fernandez, C. (2018). The more the merrier? Number of reviews versus score on TripAdvisor and Booking.com. *International Journal of Hospitality & Tourism Administration, 21*(1), 1–14. https://doi.org/10.1080/15256480.2018.1429337
Mehraliyev, F., Chan, I. C. C., & Kirilenko, A. P. (2022). Sentiment analysis in hospitality and tourism: A thematic and methodological review. *International Journal of Contemporary Hospitality Management, 34*(1), 46–77. https://doi.org/10.1108/IJCHM-02-2021-0132
Mele, C., & Russo-Spena, T. (2022). The architecture of the phygital customer journey: A dynamic interplay between systems of insights and systems of engagement. *European Journal of Marketing, 56*(1), 72–91. https://doi.org/10.1108/EJM-04-2019-0308
Meng, Y., Khan, A., Bibi, S., Wu, H., Lee, Y., & Chen, W. (2021). The Effects of COVID-19 Risk Perception on Travel Intention: Evidence From Chinese Travelers. *Frontiers in psychology, 12*(16). https://doi.org/10.3389/fpsyg.2021.655860
Mendes-Filho, L., Mills, A. M., Tan, F. B., & Milne, S. (2018). Empowering the traveler: An examination of the impact of user-generated content on travel planning. *Journal of Travel & Tourism Marketing, 35*(4), 425–436. https://doi.org/10.1080/10548408.2017.1358237
Mensah, E. A., & Boakye, K. A. (2021). Conceptualizing Post-COVID 19 Tourism Recovery: A Three-Step Framework. *Tourism Planning & Development, 20*(1), 37–61. https://doi.org/10.1080/21568316.2021.1945674
Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., & Simkin, L. (2018). Big Data, big decisions: The impact of Big Data on board level decision-making. *Journal of Business Research, 93*, 67–78. https://doi.org/10.1016/j.jbusres.2018.08.029
Mohseni, S., Jayashree, S., Rezaei, S., Kasim, A., & Okumus, F. (2018). Attracting tourists to travel companies' websites: The structural relationship between website brand, personal value, shopping experience, perceived risk and purchase intention. *Current Issues in Tourism, 21*(6), 616–645. https://doi.org/10.1080/13683500.2016.1200539
Morar, C., Tiba, A., Basarin, B., Vujičić, M., Valjarević, A., & Niemets, L. (2021). Predictors of changes in travel behavior during the COVID-19 pandemic: The role of tourists' personalities. *International Journal of Environmental Research and Public Health, 18*(21), 11169. https://doi.org/10.3390/ijerph182111169
Mourtzis, D., Panopoulos, N., Angelopoulos, J., Wang, B., & Wang, L. (2022). Human centric platforms for personalized value creation in metaverse. *Journal of Manufacturing Systems, 65*, 653–659. https://doi.org/10.1016/j.jmsy.2022.11.004
Moya, C., Kline, M. A., & Smaldino, P. E. (2020). Dynamics of behavior change in the COVID world. *American Journal of Human Biology, 32*(5), E23485. https://doi.org/10.1002/ajhb.23485
Mir-Bernal, P., Guercini, S., & Sádaba, T. (2017). The role of e-commerce in the internationalization of Spanish luxury fashion multi-brand retailers. *Journal of Global Fashion Marketing, 9*(1), 59–72. https://doi.org/10.1080/20932685.2017.1399080
Miranda, S., Berente, N., Seidel, S., Safadi, H., & Burton-Jones, A. (2022). Editor's comments: Computationally intensive theory construction: A primer for authors and reviewers. *MIS Quarterly, 46*(2), 3–18.
Mufti, O., Parvaiz, G. S., & Ullah, U. (2018). Creating Distinctiveness & Vividness in Ads Using Isolation Effect: A Case of Cellular Network Providers. *Journal of Managerial Sciences, 12*(1). Retrieved from https://www.qurtuba.edu.pk/jms/default_files/JMS/12_1/9.pdf.
Mustapha, I., Khan, N., & Qureshi, M. I. (2022). Is technology affecting the way our minds operate? Digital psychology of users in the era of digitalization. In A. Ismail, M. A. MohdDaril, & A. Öchsner (Eds.), *Advanced transdisciplinary engineering and technology. advanced structured materials* (pp. 71–92). Cham: Springer. https://doi.org/10.1007/978-3-031-01488-8_8, 174.
Myoung-a, A., & Sang-Lin, H. (2020). Effects of experiential motivation and customer engagement on customer value creation: Analysis of psychological process in the experience-based retail environment. *Journal of Business Research, 120*, 389–397. https://doi.org/10.1016/j.jbusres.2020.02.044
Negahban, A., & Yilmaz, L. (2014). Agent-based simulation applications in Marketing Research: An integrated review. *Journal of Simulation, 8*(2), 129–142. https://doi.org/10.1057/jos.2013.21
Nasir, S. A., Ali, Ausaf, Zuguang, Shi, Ziting, He, & Ammar, Yasir (2022). Technology & Behavioral Changes Mediation for Personnel Safety Intentions: Crisis in theoretical framework. *International Journal of Information Management Data Insights, 2*(2), Article 100137. https://doi.org/10.1016/j.jjimei.2022.100137. Available at:.
Obembe, D., Demola, O., Oluwaseun, K., Funmi, O., Adebowale, O., & Oluwasoye, M. (2021). COVID-19 and the tourism industry: An early stage sentiment analysis of the impact of social media and stakeholder communication. *International Journal of Information Management Data Insights, 1*(2), Article 100040. https://doi.org/10.1016/j.jjimei.2021.100040. Available at:.
Okafor, L., Khalid, U., & Moreno Gama, L. E. (2022). Do the size of the tourism sector and level of digitalization affect COVID-19 economic policy response? Evidence from developed and developing countries. *Current Issues in Tourism*. https://doi.org/10.1080/13683500.2022.2107898
Oliveira, T., Araujo, B., & Tam, C. (2020). Why do people share their travel experiences on social media? *Tourism Management, 78*, Article 104041. https://doi.org/10.1016/j.tourman.2019.104041
Orea-Giner, A., Fuentes-Moraleda, L., Villacé-Molinero, T., Muñoz-Mazón, A., & Calero-Sanz, J. (2022). Does the implementation of robots in hotels influence the overall TripAdvisor rating? A text mining analysis from the industry 5.0 approach. *Tourism Management, 93*, Article 104586. https://doi.org/10.1016/j.tourman.2022.104586
Ozuem, W., Ranfagni, S., Willis, M., Rovai, S., & Howell, K. (2021). Exploring customers' responses to online service failure and recovery strategies during COVID-19 pandemic: An actor–network theory perspective. *Psychology & Marketing, 38*(9), 1440–1459. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1002/mar.21527.
Pardo, C., & Ladeiras, A. (2020). COVID-19 "tourism in flight mode": A lost opportunity to rethink tourism – towards a more sustainable and inclusive society. *Worldwide Hospitality and Tourism Themes, 12*(6), 671–678. https://doi.org/10.1108/WHATT-07-2020-0064
Peng, M., Xu, Z., & Huang, H. (2021). How does information overload affect consumers' online decision process? An event-related potentials study. *Frontiers in Neuroscience, 15*, Article 695852. https://doi.org/10.3389/fnins.2021.695852
Pencarelli, T., Gabbianelli, L., & Savelli, E. (2021). The tourist experience in the digital era: The case of Italian millennials. *Sinergie Italian Journal of Management, 38*, 165–190. https://doi.org/10.7433/s113.2020.10
Pillai, S. G., Haldorai, K., Seo, W. S., & Kim, W. G. (2021). COVID-19 and hospitality 5.0: Redefining hospitality operations. *International Journal of Hospitality Management, 94*. https://doi.org/10.1016/j.ijhm.2021.102869
Proctor, R. W., & Schneider, D. W. (2018). Hick's law for choice reaction time: A review. *Quarterly Journal of Experimental Psychology, 71*(6), 1281–1299. https://doi.org/10.1080/17470218.2017.1322622
Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing, 28*(3), 181–193. https://doi.org/10.1016/j.ijresmar.2011.04.002
Rao, R. J., Christopher, S., Arnulfo, P., & Siva, M. R. (2018). Assessing Learning Behavior and Cognitive Bias from Web Logs. In *2018 IEEE Frontiers in Education Conference (FIE). ieeexplore.ieee.org* (pp. 1–5).
Reklitis, P., Ioannis, M., Elisavet, M., & Panagiotis, T. (2017). Employee perceptions of corporate social responsibility activities and work-related attitudes: The case of a

Greek management services organization. *Accounting, Finance, Sustainability, Governance & Fraud: Theory and Application*, 225–240. https://doi.org/10.1007/978-981-10-4502-8_10

Roetzel, P. G. (2019). Information overload in the information age: A review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. *Business research, 12*(2), 479–522. https://doi.org/10.1007/s40685-018-0069-z

Saheb, T., Amini, B., & Alamdari, F. K. (2021). Quantitative analysis of the development of digital marketing field: Bibliometric analysis and network mapping. *International Journal of Information Management Data Insights, 1*(2), Article 100018.

Sajid, S., Rashid, R. M., & Haider, W. (2022). Changing Trends of Consumers' Online Buying Behavior During COVID-19 Pandemic With Moderating Role of Payment Mode and Gender. *Frontiers in psychology, 10*. https://doi.org/10.3389/fpsyg.2022.919334

Sakas, D. P., & Reklitis, D. P. (2021). The Impact of Organic Traffic of Crowdsourcing Platforms on Airlines' Website Traffic and User Engagement. *Sustainability*. https://www.mdpi.com/1220792.

Sakas, D. P., Reklitis, D. P., Trivellas, P., Vassilakis, C., & Terzi, M. C. (2022a). The effects of logistics websites' technical factors on the optimization of Digital Marketing Strategies and corporate brand name. *Processes, 10*(5), 892. https://doi.org/10.3390/pr10050892

Sakas, D. P., Reklitis, D. P., Terzi, M. C., & Vassilakis, C. (2022b). Multichannel Digital Marketing Optimizations through Big Data Analytics in the Tourism and Hospitality Industry. *Journal of Theoretical and Applied Electronic Commerce Research, 17*(4), 1383–1408. https://doi.org/10.3390/jtaer17040070. Retrieved from.

Sasaki, Akira, Xiang, Fu, Hayashi, Rina, Hiramatsu, Yuko, Ueda, Kazutaka, & Harada, Yasunari (2020). A Study on the Development of Tourist Support System Using ICT and Psychological Effects. *Applied Sciences, 10*(24), 8930. https://doi.org/10.3390/app10248930

Saura, J. R. (2021). Using Data Sciences in Digital Marketing: Framework, methods, and performance metrics. *Journal of Innovation & Knowledge, 6*(2), 92–102. https://doi.org/10.1016/j.jik.2020.08.001

Saura, J. R., Palos-Sánchez, P., & Cerdá Suárez, L. M. (2017). Understanding the digital marketing environment with Kpis and web analytics. *Future Internet, 9*(4), 76. https://doi.org/10.3390/fi9040076

Saxena, D., & Lamest, M. (2018). Information overload and coping strategies in the big data context: Evidence from the hospitality sector. *Journal of Information Science, 44*. https://doi.org/10.1177/0165551517693712

Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and tourism online reviews: Recent trends and future directions. *Journal of Travel & Tourism Marketing, 32*(5), 608–621. https://doi.org/10.1080/10548408.2014.933154

Semrush. (2019). *Semrush traffic analytics 101: Analyzing competitors' traffic manual - semrush toolkits*. *Semrush*. Retrieved November 24, 2022, from https://www.semrush.com/kb/895-traffic-analytics-overview-report.

Sharma, R., Kumar, A., & Chuah, C. (2021). Turning the blackbox into a glassbox: An explainable machine learning approach for understanding hospitality customer. *International Journal of Information Management Data Insights, 1*(2), Article 100050.

Sharma, S., Rana, V., & Kumar, V. (2021). Deep learning based semantic personalized recommendation system. *International Journal of Information Management Data Insights, 1*(2), Article 100028.

Siegel, L. A., & Wang, D. (2019). Keeping up with the joneses: Emergence of travel as a form of social comparison among millennials. *Journal of Travel and Tourism Marketing, 36*(2), 159–175. https://doi.org/10.1080/10548408.2018.1499579

Sigala, M. (2020). Tourism and COVID-19: Impacts and implications for advancing and resetting industry and research. *Journal of Business Research, 117*, 312–321. https://doi.org/10.1016/j.jbusres.2020.06.015

Silva, P. C., Batista, P. V., Lima, H. S., Alves, M. A., Guimarães, F. G., & Silva, R. C. (2020). Covid-abs: An agent-based model of COVID-19 epidemic to simulate health and economic effects of social distancing interventions. *Chaos, Solitons & Fractals, 139*, Article 110088. https://doi.org/10.1016/j.chaos.2020.110088

Simonov, A., Nosko, C., & Rao, J. M. (2018). Competition and crowd-out for brand keywords in sponsored search. *Marketing Science, 37*(2), 200–215. https://doi.org/10.1287/mksc.2017.1065

Singh, V., Shiuann, S. C., Minal, S., Brijesh, N., Arpan, K. K., & Agam, G. (2022). How are reinforcement learning and deep learning algorithms used for big data based decision making in Financial Industries–a review and Research Agenda. *International Journal of Information Management Data Insights, 2*(2), Article 100094. https://doi.org/10.1016/j.jjimei.2022.100094

Škare, M., Riberio-Soriano, R., & Porada-Rochoń, M. (2021). Impact of COVID-19 on the travel and tourism industry. *Technological Forecasting and Social Change, 163*. https://doi.org/10.1016/j.techfore.2020.120469

Soltani-Nejad, N., Rastegar, R., Shahriari-Mehr, G., & Taheri-Azad, F. (2022). Conceptualizing tourist journey: Qualitative analysis of tourist experiences on TripAdvisor. *Journal of Quality Assurance in Hospitality & Tourism*, 1–22. https://doi.org/10.1080/1528008x.2022.2124575

Stoeckel, F., Stöckli, S., Phillips, J., Lyons, B., Mérola, V., Barnfield, M., et al. (2022). Stamping the vaccine passport? Public support for lifting COVID-19 related restrictions for vaccinated citizens in France, Germany, and Sweden. *Vaccine, 40*(38), 5615–5620. https://doi.org/10.1016/j.vaccine.2022.08.009

Suha, S. A., & Sanam, T. F. (2023). Exploring dominant factors for ensuring the sustainability of utilizing artificial intelligence in healthcare decision making: An emerging country context. *International Journal of Information Management Data Insights, 3*(1), Article 100170.

Taecharungroj, V., & Mathayomchan, B. (2019). Analysing TripAdvisor reviews of tourist attractions in Phuket, Thailand. *Tourism Management, 75*, 550–568. https://doi.org/10.1016/j.tourman.2019.06.020

Tan, W., & Kuo, P. (2019). The consequences of online information overload confusion in tourism. *Inf. Res., 24*. Retrieved from http://informationr.net/ir/24-2/paper826.html.

Terzić, A., Petrevska, B., & DemirovićBajrami, D. (2022). Personalities shaping travel behaviors: Post-COVID scenario. *Journal of Tourism Futures*. https://doi.org/10.1108/JTF-02-2022-0043. Vol. ahead-of-print No. ahead-of-print.

Tokmak, G. (2019). Tüketimde Diderot Etkisive Zeigarnik EtkisineKavramsal BirBakış. *TUJOM, 4*(1), 42–61. https://doi.org/10.30685/tujom.v4i1.39

Touni, R., Kim, W. G., Choi, H. M., & Ali, M. A. (2020). Antecedents and an outcome of customer engagement with hotel brand community on Facebook. *Journal of Hospitality & Tourism Research, 44*(2), 278–299. https://doi.org/10.1177/1096348019895 5

Umesh, U. N., & Kagan, M. (2015). Data Visualization in Marketing. *Journal of Marketing Management, 3*(2), 39–46. Retrieved from http://jmm-net.com/journals/jmm/Vol_3_No_2_December_2015/4.pdf.

Unhelkar, B., Joshi, S., Sharma, M., Prakash, S., Mani, A. K., & Prasad, M. (2022). Enhancing supply chain performance using RFID technology and decision support systems in the industry 4.0–A systematic literature review. *International Journal of Information Management Data Insights, 2*(2), Article 100084.

Vannucci, V., & Pantano, E. (2020). Insights from consumer-facing in-store services. *Information Technology & People, 33*(1), 296–310. https://doi.org/10.1108/ITP-02-2018-0113

Vila, T. D., González, E. A., Vila, N. A.&, & Brea, J. A. F. (2021). 2021) Indicators of Website Features in the User Experience of E-Tourism Search and Metasearch Engines. *J. Theor. Appl. Electron. Commer. Res., 16*, 18–36. https://doi.org/10.4067/S0718-18762021000100103

Vyas, C. (2019). Evaluating state tourism websites using search engine optimization tools. *Tourism Management, 73*, 64–70. https://doi.org/10.1016/j.tourman.2019.01.019

Ward, P. R. (2020). A sociology of the Covid-19 pandemic: A commentary and research agenda for sociologists. *Journal of Sociology, 56*(4), 726–735. https://doi.org/10.1177/1440783320939682

World Health Organization (2022). WHO Coronavirus (COVID-19) Dashboard. Retrieved from https://covid19.who.int/ (accessed on 1 November 2022).

Xu, X., & Schrier, T. (2019). Hierarchical effects of website aesthetics on customers' intention to book on Hospitality sharing economy platforms. *Electronic Commerce Research and Applications, 35*, Article 100856. https://doi.org/10.1016/j.elerap.2019.100856

Yachin, J. M. (2018). The 'customer journey': Learning from customers in tourism experience encounters. *Tourism management perspectives, 28*, 201–210. https://doi.org/10.1016/j.tmp.2018.09.002

Yallop, A., & Seraphin, H. (2020). Big data and analytics in tourism and hospitality: Opportunities and risks. *Journal of Tourism Futures, 6*(3), 257–262. https://doi.org/10.1108/JTF-10-2019-0108

Zajenkowski, M., Jonason, P. K., Leniarska, M., & Kozakiewicz, Z. (2020). Who complies with the restrictions to reduce the spread of COVID-19?: Personality and perceptions of the COVID-19 situation. *Personality and individual differences, 166*, Article 110199. https://doi.org/10.1016/j.paid.2020.110199

Zaman, M., Botti, L., & Vo-Thanh, T. (2016). Weight of criteria in hotel selection: An empirical illustration based on TripAdvisor Criteria. *European Journal of Tourism Research, 13*, 132–138. https://doi.org/10.54055/ejtr.v13i.236

Zhang, L., Zeng, X., Morrison, A. M., Liang, H., & Coca-Stefaniak, J. A. (2022). A risk perception scale for travel to a crisis epicentre: Visiting Wuhan after COVID-19. *Current Issues in Tourism, 25*(1), 150–167. https://doi.org/10.1080/13683500.2020.1857712

Zizic, M. C., Mladineo, M., Gjeldum, N., & Celent, L. (2022). From Industry 4.0 towards Industry 5.0: A Review and Analysis of Paradigm Shift for the People, Organization and Technology. *Energies, 15*(14), 5221. https://doi.org/10.3390/en15145221