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ASSESSING DESTINATION BRAND ASSOCIATIONS ON TWITTER: THE CASE OF ISTANBUL

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ABSTRACT

The development of data mining has paved the way for studies that identify brand associations from user-generated content (UGC). However, the number of studies investigating destination associations with social media is limited. The aim of this study is to explore destination associations with UGC on Twitter and to show how data mining and sentiment analysis methods can be applied to destinations to elicit brand associations. In this study, 33,339 English-language tweets containing the word #Istanbul were collected over one year and analyzed using text mining (association rule analysis) and sentiment analysis. As a result of the study, a brand concept map (BCM) of what Twitter users associate with Istanbul was created and compared to other studies that measure associations using conventional methods. The main results show that users have positive associations with tourism in Istanbul. Unique and interesting associations (such as "cats") were observed compared to other previous studies that measured associations to destinations. Based on the study results, a method was proposed for measuring the image of a place brand by observing electronic word of mouth in social media.

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INTRODUCTION

Social media is an effective platform for shaping consumers' destination perception and travel decisions (di Pietro et al., 2012). Word of mouth (WOM) plays an important role in building a destination's brand image

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with the widespread use of social media on electronic platforms. Social media has created a new environment for social interaction that makes WOM visible and accessible. The most important advantage of WOM is being spontaneous and free expression (Alzate et al., 2022). UGC contains large amounts of data about users' thoughts and feelings which is also a powerful and valuable source for researchers (Wong & Qi, 2017). For this reason, UGC is preferred by many researchers in determining brand associations.

Data mining offers great opportunities to obtain meaningful results from unstructured social media data. The fact that UGC is big and unstructured data makes data analysis very difficult (Kiran & Vasantha, 2016). With the development of data mining, unstructured social media data can be configured in accordance with the analysis (Diaz-Garcia et al., 2022). Currently, sentiment analysis techniques allow us to determine favorability (consumers' positive or negative feelings toward brand associations) (Mitra & Jenamani, 2020). Recent technologies in Big Data analytics have paved the way for faster data collection, processing, and analysis (Oliverio, 2018). A limited number of studies have attempted to investigate the perception of destination brands on Twitter. However, there is still a significant gap for new studies to measure destination associations on social media. Therefore, this gap was the starting point for this study.

Brand Concept Maps (BCM) are an effective way to measure and visualize the strength, uniqueness, and favorability of brand associations. Thanks to text mining techniques, BCMs can be created from unstructured social media content. Therefore, this study attempts to add a new dimension to the BCM technique, which is rarely used in the tourism literature, by measuring the association network of destination brands using Twitter data. This method can play a key role in crafting messages for use in brand communication strategies and in decision making by showing destination managers which associations to use to position their brand and which negative associations to eliminate.

Understanding associations is an important issue for brand communication plans of destination marketing organizations. Marketers use brand association to differentiate, position, and extend the brand, as well as to develop positive attitudes and emotions toward it (Low & Lamb, 2000). In recent years, many destinations have been promoted through social media. In order to conduct an advertising campaign on social media, data measured through social media is required. This study will also allow to determine the concepts that can be used in creating the messages that practitioners need for brand communication. Traditional methods such as surveys have been used in previous studies of destination association, but few studies were found that used social media data.

In this study, Twitter users' perceived associations with travel destinations are determined. A method was proposed to measure the associations with a destination's brand by observing WOM in social media. The objective of this study is to (1) demonstrate that the BCM technique can be applied in evaluating travel destination brand associations by using unstructured data sources; (2) draw attention to the fact that social media is a powerful data source in exploring travel destination associations; (3) demonstrate how to explore a travel destination's brand association network using data mining and sentiment analysis on Twitter. It is expected that mining data from Twitter and creating a BCM in accordance with the analysis performed by the data mining and sentiment analysis method will provide a new perspective for destination branding researchers.

LITERATURE REVIEW

Conceptual and Theoretical Background

Associations have long been a topic of interest in brand research. Aaker (1991, p. 109) defines brand associations as everything that is associated with the brand in the consumer's mind. To generate favorable feelings for a brand, highlight the advantages of utilizing it, and market a specific brand, brand managers employ brand associations in brand positioning and brand extension strategies (Low & Lamb, 2000).

The cornerstones of consumer-based brand equity and brand image are brand associations. (Christodoulides & de Chernatony, 2010). Biel (1992, p. 71) describes a brand's image as a collection of traits and connections that customers connect with the name of the company. According to Keller (2013, p. 549), a positive brand image is created by associating strong, favorable and unique associations to the brand in the mind. This statement allows to depict brand image as a network of brands and associations in the customer's mind (Dirsehan & Kurtuluş, 2018). Brand associations are theoretically based on Associative Network Theory. According to the theory, memory is a network of interconnected nodes that activate in related contexts and these nodes are linked to each other in a network of relationships (Anderson & Bower, 1980). Concepts are represented as nodes in this network, and the relationship of concepts to each other is represented as links (Collins & Loftus, 1975; Teichert & Schöntag, 2010). Whether brand associations are positive or negative, their uniqueness is a process that needs to be well managed. Therefore, an in-depth exploration of consumers' association networks provides brand managers with valuable insights.

Measuring Brand Associations

Previous studies measuring brand associations have used a traditional approach, collecting data directly from the respondent, and an approach using data derived from content generated by internet users (Gensler et al., 2015). Nam et al., (2017), on the other hand, classified these approaches as primary data-based approaches (survey-interview, ZMET, BCM, sorting), text mining approaches, and social tag-based approaches. Text mining and social tagging are approaches that use UGC.

Many qualitative, quantitative, and mixed methods have been proposed in traditional studies to measure brand associations (Vriens et al., 2019; Zenker & Braun, 2015). Qualitative techniques used in measuring brand associations are "free association" (e.g., Cornwell et al., 2022; Keller, 2013; Kim, 2017; Rahman & Areni, 2016; Shams et al., 2015), and projective techniques (e.g., Cian & Cervai, 2011; Hofstede et al., 2007; Pich et al., 2015; Spry & Pich, 2021). Likert scale (Chen, 2017; Cho et al., 2015; Gorin et al., 2022; Koll et al., 2022; Phong et al., 2020; Plumeyer et al., 2019), semantic differential scale (Alexandris et al., 2008; Ciabuca, 2015), dichotomous scale (e.g., Hsieh, 2018; Lim & O'Cass, 2001), rating scales (e.g., Dillon et al., 2001; Romaniuk, 2014), sorting task (Blanchard et al., 2017) and "Pick Any" (Dolnicar et al. 2012) are quantitative methods. However, it is known today that these scales cannot be standardized and generalized to different cultural backgrounds or different contextual factors (Başfırıncı, 2016; Gensler et al., 2015). Lastly, Repertory Grid (Bell, 2005) and BCM (Goffin et al., 2010; John et al., 2006; Schnittka et al., 2012) are examples of mixed methods.

All of the methods mentioned above place more emphasis on the relationship between an attribute and a brand than on the brand associations as a network. Therefore, these approaches are insufficient to measure the strength, favorability and uniqueness of brand associations (Brandt et al., 2011). Therefore, examining brand associations as a network structure will provide a clearer understanding of brand perceptions (French & Smith, 2013).

There are two approaches to the analysis of the brand association network: analytic techniques (network analysis) and mapping techniques

(BCM-Zaltman Metaphor Elicitation Technique) (John et al., 2006). A mathematical technique called network analysis examines the connections between concepts using the parameters of centrality, cohesion, position, density, and equivalence (Henderson et al., 1998). The Zaltman Metaphor Elicitation Technique (ZMET) is a method in which a network of brand associations is revealed, especially through metaphors located in the subconscious of consumers (Zaltman, 1995). Metaphors can be explored using images such as paintings and objects to help express conscious and unconscious thoughts and emotions (Matheson & McCollum, 2008).

One of the effective methods of assessing the structure of the consumer association network is the original brand concept maps (John et al., 2006). Important contributions of the BCM method are the set of rules for collecting brand association network data created individually by each individual in a consensus map (Böger et al., 2017). Three steps make up the BCM process: elicitation, mapping, and aggregation (John et al., 2006). At the elicitation step, brand associations are derived from responses to open-ended questions in which at least 50% of the participants cited a specific brand. Each respondent is required to create a map by connecting the concepts with one to three lines, depending on the strength of the associations, during the mapping stage. The original BCM, which shows the strength and uniqueness of brand associations, does not reflect how associations are evaluated by the consumer. Schnittka et al. (2012) further extended the scope of BCM, which measures the strength and uniqueness of associations, and developed the brand association network value metric to show the favorable associations on the map. In this mapping, the degree of negative evaluation of associations is stated by the darkness of the color of the circles surrounding the association (Schnittka et al., 2012).

Mapping techniques using qualitative and quantitative methods have weaknesses such as the tendency to choose answers that respondents believe are more socially desirable or acceptable, the validity and reliability problems of the survey and interview method, and the laboriousness and vapidity of individual data collection (Nam et al., 2017). UGCs, on the other hand, are powerful data sources where users generate data voluntarily, without influence or intervention from the researcher (Culotta & Cutler, 2016; Divakaran & Xiong, 2022).

Approaches Using User-Generated Content

Currently, data collection has evolved into an understanding in which responders are personally observed in the interaction environment without any guidance. Digital transformation also manifests itself in brand research. Therefore, researchers are seeking brand associations not in the answers that the consumer gives to questionnaire or interview questions, but in the content that the consumer creates herself/himself.

Web 2.0 provides gathering platforms for internet users in social media. Consumers leave an enormous footprint in these platforms about their thoughts, beliefs, experiences, and even interactions (Netzer et al., 2012). Customers voluntarily use social networking websites and share pertinent information in public. The publicly sharing of UGC has opened a door for researchers to hear the voice of the consumer (Klostermann et al., 2018). UGC is generally a useful information source because it is unbiased and reflects unofficial consumer advice (East et al., 2008). Since consumers' opinions and sentiments about brands are readily available online, researchers can quickly gather data. Data obtained from UGC are gathered by content analysis conducted for consumers' brand associations. But manual analysis of UGC datasets is a difficult process due to the size of the data and its unstructured nature (Elsayed et al., 2019; Yan et al., 2022).

Text mining has become one of the preferred methods for uncovering brand association networks in recent years. The main reason is that the qualitative analysis and interviewing methods used in traditional methods are time-consuming and tedious, require expertise, represent a limited period of time because they are applied over a period of time, have a small sample size, and simply focus on uncovering brand associations (Nam et al., 2017).

Divakaran and Xiong (2022) qualitatively analyzed users' online comments on a movie brand, measured the uniqueness, strength, and favorability of associations, and displayed them on the BCM. The BCM was created by measuring the frequency (strength) of associations, the level of difference of associations compared to competing brands (uniqueness), and the number of associations coded as positive-negative (favorability). However, this method is much more difficult and laborious for manual coding of more UGC. Advances in text mining can overcome these challenges.

Finding hidden information in textual data is a process known as text mining, a particular type of data mining (Feldman & Sanger, 2006; Miner et al., 2012). Chen (2012), on the other hand, describes text mining as the process of obtaining interesting information or insights from unstructured text. Data sources used in text mining are unstructured data obtained from expressions freely used by people in daily life (Marchand et al., 2017).

Naturel Language Processes (NLP) are the language used in daily life regardless of terms and transforms spoken words into structured data (Miner et al., 2012). Text mining mainly involves clustering, association rule analysis, trend analysis, pattern discovery, and other knowledge discovery algorithms (Zhang et al., 2015). Association Rules is a technique used in text mining to determine the causal relationships between two concepts (Lopes et al., 2007; P. C. Wong et al., 1999). A conceptually similar study was performed by Diaz-Garcia et al. (2022) who emphasized that association rule mining provides interpretability of the research model and results in social media mining.

Sentiment Analysis, an important area of text mining, is the detection of some text to be positive, neutral, or negative in meaning (Howells & Ertugan, 2017) and currently preferred in many studies to determine the favorability of brand associations (Karayılmazlar et al., 2019; Mishra & Sharma, 2019; Mitra & Jenamani, 2020; Yang et al., 2022). Sentiment analysis is therefore a functional method for measuring the favorability of brand associations.

There is an increasing trend toward the use of text mining in brand association research. For example, Netzer et al. (2012) used the frequency of co-occurrence of concepts and lift value to reveal brand associations and to measure the strength of the relationship between associations. Mitra and Jenamani (2020) proposed measuring the favorability, strength, and uniqueness of brand associations from consumer reviews using the text mining technique. According to Culotta and Cutler (2016), text mining offers a reliable, adaptable, and scalable method for tracking brand perceptions. Similarly, Liu et al. (2017) proposed a framework that automatically extracts brand topics and classifies brand sentiment by applying sentiment analysis and text mining to tweets about 20 brands in 5 different industries from UGC on social media. Blasi et al. (2020) examined the brand perceptions of fashion consumers from Twitter data using data mining method and pointed out that the survey approach has weaknesses such as the prejudices and reluctance of the respondents, and that Twitter contains more reliable opinions about brands. In another study, Park et al. (2023) used network analysis to compare the relationship between associations and different aspects of brands, to compare the differences between brands, and sentiment analysis to measure the attributes that users consider important in the product and users' evaluations. Using Latent Dirichlet Allocation and dictionary-based sentiment analysis, Alzate et al. (2022) analyzed brand image and brand positioning from online consumer reviews. In previous studies, it is seen that measuring the strength of associations, the co-occurrence of concepts in the text, and sentiment analysis were preferred in examining the favorability of associations. In this study, unlike previous studies, association rule analysis is used to calculate the strength of associations. Association rule analysis successfully applies an unsupervised data mining method and is one of the methods for detecting interesting associations from big data.

Measuring destination brand associations: from conventional methods to user-generated content

The measurement of brand associations is particularly found in studies of destination image and destination brand equity. The main reason for this is that the second fundamental element of brand equity is brand association (e.g. Aaker, 1992; Christodoulides & de Chernatony, 2010; Keller, 1993). Another approach is to use brand associations as a substitute for brand image. For example, Cai (2002) defines destination brand image as the perception reflected by the place-related associations in the memory of tourists. Kladou and Kehagias (2014) suggest that destination brand association is generally used in place of or represents brand image, while Bianchi et al. (2014) emphasize that destination brand associations relate to the image of the destination brand. In addition, Stepchenkova and Li (2014) argue that destination associations are one of the key elements of destination brand image.

In the traditional methods used to measure destination association, standardized questionnaires and free association techniques are mainly used. In these studies of tourism destinations, image is generally conceptualized as a structure consisting of two dimensions: the affective image and the cognitive image (Baloglu & McCleary, 1999; Gartner, 1994; Gartner & Ruzzier, 2010; Huete-Alcocer & Hernandez-Rojas, 2022). Pike (2009) proposed that destination associations should be measured as part of the cognitive, affective, and behavioral components of the image. Furthermore, Qu et al. (2011) pointed out that uniqueness should be included in addition to these aspects to measure destination brand association. Sahin and Baloglu (2011) analyzed the brand image of Istanbul based on common image components or characteristics, expected atmosphere, unique and popular tourist attractions, tourist activities, with an approach similar to the BCM technique. However, measuring destination associations with standardized questionnaires is limited to defined dimensions (Zenker & Braun, 2015). The common conclusion of these approaches is that positive or negative assessments of associations and uniqueness of associations are important factors that must be assessed when measuring a destination's brand. However, these studies did not focus on the direct eliciting of destination associations and associative network structures.

Different customer groups have different expectations and complex structured destination brand associations. Due to this problem, previous studies tend to use BCMs, which are an effective method to measure the association network structure of destination brands (Zenker & Braun, 2017). Another approach used in measuring destination associations are association network mapping techniques. For example, Zenker (2014) measured the strength, favorability and uniqueness of associations using the Advanced BCM technique, which is based on the Keller’s (1993) approach. Brandt and de Mortanges (2011) tested the applicability of the BCM technique to place brands by measuring city brand associations. Using BCMs and network analysis, Ci and Choi (2017) proposed a method for comparing a place's image and place identity. Ivanov et al. (2010), combining the destination brand molecule and BCM techniques, examined the brand perception of two different destinations and argued that this technique reflects the dominant perceptions of the participants. By examining three different destinations with a BCM, Ibrahim and Elborsaly (2022) also show that it closes the gap in traditional measurements and provides a valid tool to explore the strengths and weaknesses of brand associations.

Recently, there has been an increasing interest in UGCs as a data collection method in destination associations retrieval. For example, Alarcón-Urbistondo et al. (2021) have suggested using UGC in destination image research, as it contains rich current information, is easily accessible, and is a low-cost data source. Marine-Roig and Anton Clavé (2015) analyzed the UGC in travel blogs by text mining and stated that it provides interesting results for brand architecture in a complex destination. Költringer and Dickinger (2015) also argue that the UGC is the richest and most diverse online source of information. Choi et al. (2015) and Mak (2017) applied content analysis with the help of text mining to reveal the destination image from websites and blogs. Liu et al. (2021) analyzed the tourists' comments about Macau on travel blogs by using text mining techniques.

Moreover, measuring the favorableness of travel destination associations through sentiment analysis is becoming more widespread (Clarke & Hassanien, 2020; Jiang et al., 2021; Nadeau et al., 2021; Park et al., 2020; Ren & Hong, 2017; Surugiu et al., 2021; Tseng et al., 2015). Kim et al.

(2017) observed that sentiment analysis in destination brand research is a more economical and less time-consuming method than survey method in predicting the favorability of brands. Jiang et al. (2021) measured the destination image of Hong Kong from the reviews of tourism websites and suggested that sentiment analysis provides a deeper understanding of the destination image. However, studies measuring travel destination associations using UGC data are generally focused on forum sites and travel blogs, and few studies used Twitter.

Measuring Destination Brand Associations on Twitter

The realization of conventional WOM communication in an electronic environment further increases the importance of social media in place branding. Kavaratzis (2004) argues that the brand of the city is transmitted in primary, secondary, and tertiary ways. Primary communication is the physical and managerial characteristics of the place. Secondary communication is formal brand communication such as marketing communications. Tertiary communication is WOM communication that occurs as a result of primary and secondary communication (Kavaratzis, 2004). WOM communication is an important component that affects the brand image and cannot be controlled by city managers. Therefore, analyzing the data obtained from WOM communication or tertiary communication of the place branding will provide more accurate results for the destination image. Social media has a significant impact on destination branding via its eWOM communication feature.

Twitter is an important E-WOM platform that enables brands to get insight (Burkhalter et al., 2014; Hodeghatta & Sahney, 2016). Twitter gives an idea of how users react to critical decision-making and to purchasing products by showing immediate sensitivity to a topic (Jansen et al., 2009) and provides researchers with big data on how much and how a brand interacts. The identification of intriguing, unexpected, or noteworthy structures from large datasets is the key component of data mining (Hand, 2007). On the other hand, as a platform of thought sharing, Twitter is an open-source database and its feature of sharing based on the text enables researchers to collect and analyze data more easily and quickly (Nadeau et al., 2021).

The use of Twitter as a data source, which has a significant impact on tourists' decision-making, is rapidly increasing in tourism research (Curlin et al., 2019). Table 1 shows that studies measuring Twitter users' perceptions of destinations focus on destination perception or satisfaction rather than measuring brand associations. Machine learning and dictionary-based sentiment analysis are considered prominent among the methods used in these studies. In recent studies, sentiment analysis on Twitter has become a growing trend. Three different sentiment analysis methods are used in the tourism literature: machine learning, dictionary-based, and hybrid (Alaei et al., 2017). In the case of machine learning-based methods, the system is trained with pre-labeled training data and emotion classification is performed with the trained system (Flores-Ruiz et al., 2021; Paolanti et al., 2021; Shimada et al., 2011; Viñán-Ludeña & de Campos, 2022). The dictionary-based approach relies on the sentiment dictionary, which is a set of known and precompiled sentimental terms (Becken et al., 2020; Zhang et al., 2022). The hybrid approach is based on a combination of a machine learning approach and a dictionary-based methods, which is used together with the sentiment dictionary in procedures (Claster et al., 2013). Moreover, deep learning has gained popularity in recent years. It should also be noted that sentiment analysis was used to track changes in users' perception of Twitter between cyclical and normal time periods.

However, the BCM evaluation model was not used to visualize the concepts emerging from the analyses. Instead of measuring the strength-favorability and uniqueness of associations, the articles focused on thematic analysis. There are few studies that aim to elicit destination associations. For example, Andéhn et al. (2014) applied a thematic analysis based on word frequency and occurrence to measure the brand equity of Stockholm on Twitter. This study classified brand associations of the destination to specific themes. However, this study did not focus on the strength and favorableness of associations.

Unlike others, Nautiyal et al. (2022) classified the hashtags shared by Twitter users and the destination management organization into different topics and analyzed the content of the regional tourism organization and locals and international Twitter users in comparison. In some previous studies, visual content was used as data in addition to text. Bui et al. (2022) argue that textual data is not sufficient to explain the destination brands. For this reason, the visual and textual data collected from social networks (Flicker, Twitter, etc.) via API set and web crawling tool were classified by popularity, sensitivity, time and location characteristics using the developed classification module.

Table 1. *Previous studies on measuring destination associations on Twitter*

Authors (Year)	Research Tools/ Method	Data Type	Objective	Data reporting and visualization
Bui et al. (2022)	Construct popularity measurement / Word frequency, text classification, topic analysis Textual and visual sentiment analysis / aspect-oriented sentiment analysis	Textual and visual	To measure tourism destination image from unstructured big data and develop a holistic measurement framework.	heat-map, semantic graph, charts, and tables
Leelawat et al. (2022)	Term frequency Sentiment Analysis / Machine learning-based	Textual data	To monitor tourists' moods and visit intentions towards Thailand during the Covid 19 pandemic period.	WordCloud, graph, charts, and tables
Nautiyal et al. (2022)	Content analysis/ Classifying hashtags according to their attributes and location using cross-tabulation	Hashtags	To categorize the hashtags shared by Twitter users and the destination management organization into different topics and analyzed the content of the regional tourism organization and locals and international Twitter users in comparison	tables and charts
Viñán-Ludeña & de Campos (2022)	Sentiment Analysis/ Deep learning based	Textual data	By utilizing sentiment analysis techniques on the information gathered from Twitter and Instagram, to develop an information infrastructure for managers to enhance the perception of a tourism destination.	figures, tables
Zhang et al. (2022)	Latent Dirichlet Allocation Term Frequency-Inverse Document Frequency Sentiment Analysis/ Dictionary based	Textual data	Assessing Beijing's international image on Twitter and providing data support for destination managers' communication strategies	graph, charts, and tables
Flores-Ruiz et al. (2021)	Sentiment Analysis / Machine learning-based	Textual data	Matching current Twitter users' perceptions of the destination with the results of the Destination Management Organization's survey in the Covid-19 pandemic and observing the change in destination image.	Word cloud charts, figures, tables
Paolanti et al. (2021)	Sentiment Analysis/ Deep learning	Textual data	To compare the performances of four different classification algorithms used in sentiment analysis.	statistical graphics, plots, information graphics
Becken et al. (2020)	Sentiment Analysis / Dictionary based	Textual data - Meta data	Analyzing metadata, testing Twitter's reliability in measuring destination satisfaction.	figures, tables
Yan et al. (2020)	Sentiment analysis/ Dictionary based Latent dirichlet Allocation	Textual data	Evaluating the recovery level of tourism destinations after a disaster.	charts, figures, tables
Garay (2019)	Quantitative content analysis/ Coding	Textual data	To evaluate the relationships between destination image on Twitter by separating them according to cognitive and affective characteristics.	Word cloud

Perez Cabañero et al. (2020)	Sentiment Analysis/dictionary based (Meaning Cloud)	Textual data	To show how the photos, links, hashtags, and bookmarks in a tweet can be used to anticipate eWOM activity.	table
Andéhn et al. (2014)	Leximancer/ content (thematic-semantic) analysis	Textual data	To present an approach that reveals how Twitter is influential in the formation of place brand equity and its relational structure in a concept map by revealing place brand associations.	concept map
Claster et al. (2013)	Sentiment Analysis / hybrid -based	Textual data	Demonstrate the utility of reliable and real-time shares in tweets by current and potential consumers in market intelligence with sentiment analysis.	self-organizing map
Shimada et al. (2011)	Sentiment Analysis / Machine learning-based	Textual data	To propose a method for the information system analysis of a destination	charts, figures, tables

Twitter data is also used to track seasonal or cyclical changes to destination imagery. The destination image of the two cities was evaluated by Nadeau et al. (2021) using text mining and sentiment analysis methods throughout the Covid 19 pandemic era and the pre-pandemic period on Twitter. They found that the destination image is flexible despite a noticeably higher level of fear projections for both locations. Garay (2019) categorizes the affective and cognitive attributes of Spain's destination image by creating a codebook that describes emotional states for tweets containing #visitspain.

In summary, the above literature review reveals these important gaps in the current literature:

- Although studies analyzing brand associations on Twitter through text mining have multiplied, Twitter is still a new source of data in the field of destination branding and requires new research.
- In previous studies, researchers focused more on UGC in travel blogs, but research on destination brands on Twitter received less attention.
- Previous studies have generally focused on categorizing content into different topics using content analysis. However, research is lacking to elicit the destination's brand association network and the strength of these associations.
- The BCM approach is rarely used in studies to measure the destination brand associations.

METHODOLOGY

The empirical case of Istanbul

This study focused on the city of Istanbul to demonstrate the utility of the BCM method and UGC. Istanbul is an important city in Europe as an economic, touristic, financial, educational, cultural, artistic, and historical heritage. As one of Europe's most populous metropolises (Statista, 2020), Istanbul is a melting pot of both Eastern and Western cultures. It possesses the historical and cultural heritage of the Byzantines and the Ottomans. Thus, Istanbul will be a suitable case for measuring the destination brand from social media, and deeper and unique associations can be reached about the destination.

Procedure

The associations are the building blocks of the brand image which take place in the mind of the consumer as interrelated concepts. These associations with the target brand can be strong or weak, positive or negative. Associations can be related to each other apart from the target brand. Therefore, every association in the human mind is in a network and has a complex structure. One of the important tasks in the development of brand strategies is to reveal the associations and to determine how strong and positive the associations are brand and other associations.

Therefore, the association network was revealed in a similar way to the approach of the BCM technique, which is a mixed method that measures brand associations (John et al., 2006; Schnittka et al., 2012). Today, text mining methods provide the opportunity to determine the positive or negative states of expressions with the sentiment analysis technique. In this study, the favorability of associations was determined by applying dictionary-based sentiment analysis, one of the text mining methods, to tweets tagged Istanbul and shown in the BCM. The research process is shown in Figure 1.

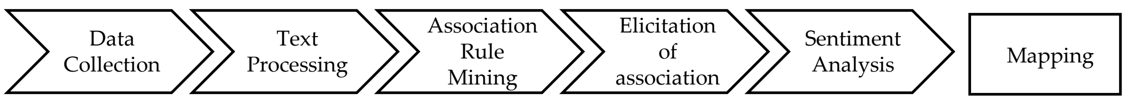

Figure 1. *Procedure*

Data Collection

English tweets that contain #Istanbul on Twitter and that were shared between June 1, 2018-31 May 2019 were collected using Rapidminer software and a total of 42.740 tweets were obtained. This number was reached by filtering retweets, posting tweets shared by robot accounts called “bot”. Bot accounts increase the access to tweets by frequently retweeting tweets. This adversely impacts the reliability of the data. In addition, tweets containing the phrases “like us”, “follow us” etc. were also removed from the data set due to their nature of ad. Two elections were held in Turkey namely presidential and national elections on June 24 March 2018 as well as local elections on March 31, 2019. Therefore, tweets on the election agenda were also shared in the range of the data collection date. Because the study focused on the associations of Istanbul's city and the statements reflected only the agenda of that year, 9189 tweets on politics and the agenda were excluded from the data set. Finally, 33.339 tweets were attained to be analyzed.

Preparing Data for Analysis

Text mining is the process of revealing hidden and useful information from text-based data (Jo, 2019). Data sources used in text mining are unstructured data obtained from expressions freely used by people in daily life. Unstructured data is complex and difficult to analyze. Text mining can analyze datasets with unstructured text content thanks to natural language processing. For this purpose, text mining can extract significant numerical indexes from text by processing the unstructured data (Özyirmidokuz, 2014). Another method used in preparing the data for analysis is to convert some words that are frequently repeated but expressed differently into a single word. Therefore, this process was carried out manually. For example, "Istanbul third airport", "Istanbul 3rd airport", "Istanbul 3rd Airport", "Istanbul's 3rd airport", "Istanbul Grand international airport", "Istanbul airport" were merged into "istanbulairport". "Blue Mosque", "Sultan Ahmet Mosque", "Sultan Ahmed Mosque", "Sultan Ahmad Mosque", are merged as "bluemosque". "Aya Sophia", "Haya Sophia", "Hagia Sophia", "Agia Sophia", "St. Sophia", "Saint Sophia", "Hagya Sophia" are merged as "hagiasophia"; "Grand Bazaar", "Grand Market" are merged as "grandbazaar"; "Spice Bazaar", "Spice Market" are merged as "spicebazaar"; "bosporus", "bosphorus" are merged as "bosphorus".

The text flow is divided into statements, words, symbols, or other significant elements by tokenization in the decomposition process, also called text pre-processing. Then, through the “transform cases” operator, all the text is converted into lower case. Prepositions, pronouns, punctuation marks and conjunctions that do not make sense alone were removed from the data set via the “Stopwords” process. In this way, the data are cleared of unnecessary words and made ready for analysis. With the help of the "Stem (snowball)" operator, words with the same root are converted into root cases. Words consisting of less than 2 to more than 25 characters are removed from the data set using the filter tokens by the length operator. The text preprocessing process applied via RapidMiner is indicated in Figure 2. Data are structured and ready for analysis with text preprocessing.

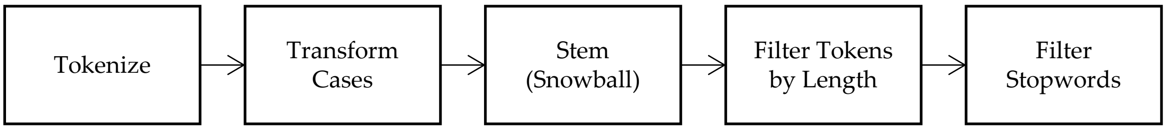

Figure 2. *Text preprocessing*

Association Rule Mining

By using association rule analysis and sentiment analysis, it is crucial to measure the strength and favorability of brand associations. In a manner similar to the BCM, associations from big data will also be shown in this manner (Schnittka et al., 2012) . The association rule, also known as market basket analysis in marketing research, is used to reveal the frequency and probability of selling products in a market together (Wong et al., 1999). In this study, the probability and the values of the words co-occuring were calculated using the association rule analysis. The association rule analysis is also similar to "contingency analysis"(Osgood, 1959). The concept of counting the co-occurrence of a word with another word as opposed to the quantity of times a word appears gave rise to contingency analysis.

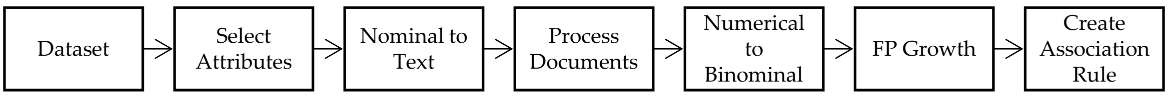

Figure 3. *Association Rule Analysis Process in Rapidminer*

The tweets were analyzed via Rapid Miner software with association analysis (Figure 3). In the association rule, the co-occurrence of two elements is symbolized as X→Y. The meaning of this rule is the probability that operations in a database containing X contain Y (Agrawal et al., 1996). The association rule is a commonly used technique for studying relationships and outcomes between subjects or descriptive concepts used to characterize structured text (Cherfi et al., 2003; Lopes et al., 2007; Rajman & Besançon, 1998). In association rule mining, two measures are used, namely "support" and "confidence". The support determines the rate at which a relationship repeats throughout the data. In an association rule, the support is defined as the percentage of document containing X∪Y in the total number of documents in the database. In Formula 1, N (X∪Y) refers to the number of documents in which X and Y contain together, and N refers to the total number of documents. So, Support (X ⇒ Y) refers to the frequency with which the concepts of X and Y in tweets coexist in all tweets. In this direction, support states the strength of the relationship between associations. Support (X ⇒ Y) is calculated as in Formula 1.

$$\text{Support } (X \Rightarrow Y) = \frac{n(X \cup Y)}{N} \qquad (1)$$

The confidence reveals the probability of customers who buy product "X" to buy product "Y". Confidence (X ⇒ Y) implies the frequency of the number of tweets where X and Y are together in tweets where X is present. For example, a result with confidence (X ⇒ Y) = 0.40 means that 40 percent of tweets containing the word "X" also contain the word "Y".

$$\text{Conf } (X) = \frac{n(X \cup Y)}{X} \qquad (2)$$

In other words, the support measure shows how frequent this correlation is in the dataset whereas the confidence measure shows the probability of the use of Y in tweets with the concept of X. Rules with a high confidence and support are called strong rules. Association rule mining requires obtaining strong patterns of co-occurrence from big databases. In association rule analysis, all frequent item sets of products must be established above a minimum support previously determined by the researcher, and strong association rules created from frequent item sets must be above a minimum support and confidence threshold determined by the user (Agrawal & Srikant, 1994). For this reason, a threshold is required for support and confidence. X⇒Y the association rule is created by the user to provide the lowest value of support and confidence (Han et al., 2012). When the minimum support is high, valuable rules cannot be obtained because they are not repeated frequently, and when the minimum support value (minsup) is low, both the number of rules increases excessively, and the importance and interestingness of the obtained rules decrease. Therefore, if the minsup is kept high, very few rules will be obtained, but if it is kept low, a large number of rules will be obtained, which occur very rarely (Lai & Cerpa, 2001). For this reason, "0.02" as the minsup threshold value and "0.7" as the minimum confidence value is preferred.

The use of support and confidence measures along with interestingness measures is recommended by many authors (McNicholas et al., 2008; Tan et al., 2018). In other words, although the rules of association show that the greater the values of support and confidence are, the stronger the relationship is, this may not always reflect the truth. Lift is the ratio of co-occurrence of two terms to the frequency expected to see them together. Therefore, when the lift value is calculated, there are three possibilities. If the lift is greater than 1, the correlation is positive, when it is less than 1, the correlation is negative. When equal to 1, the correlation is independent (Hussein et al., 2015).

Sentiment Analysis

Two approaches are used in sentiment analysis; lexicon-based and machine learning-based (Feldman & Sanger, 2006; Liu, 2010; Liu & Zhang, 2012). Machine learning approaches are supervised approaches as they perform learning over labeled training data. On the other hand, lexicon -based approaches are semi-supervised approaches that are implemented by constructing a set of terms into a sentiment dictionary. The lexicon-based approach takes advantage of a dictionary where there are known and pre-compiled terms of emotion (Medhat et al., 2014). The dictionary-based approach to sentiment analysis has been used by many researchers (Han et al., 2018; Kumar & Babu, 2021; Lopez et al., 2020). For dictionary-based sentiment analysis, it is necessary to use a dictionary that describes mood states. This study used AFINN, an English Dictionary of emotion containing 2477 words rated between -5 (negative) and 5 (positive) (Nielsen, 2011). Analysis was carried out using Phyton software.

FINDINGS

In this part of the study, the findings obtained from the association rule and sentiment analysis of English tweets containing #Istanbul are visualized in a way similar to the advanced BCM (Schnittka et al., 2012) method. As a result of the association rule analysis, 50 rules (relationships) were identified. Table 2 indicates the results for this analysis which consists of the columns, premise, conclusion, confidence value, support value, normalized support value, and lift value, respectively. If the premise is present, the probability of the conclusion is shown. Since the word "Istanbul" has been mentioned at least once in each tweet, all of the results have been included in the conclusion column. For this reason, in conventional market basket analysis, support value has become a more important measure than a confidence value because the frequency of words used together is decisive in assessing the strength of the relationship between associations. Support values are low because they are obtained from the unstructured data.

Table 2. *Findings of the association rule mining*

Associations with Istanbul	Support	Normalized Support	Confidence	Lift
Turkey	0.3237	1.0000	0.9943	1.0040
travel	0.1323	0.3802	0.9946	1.0043
turkey, travel	0.0820	0.2173	0.9975	1.0072
love	0.0728	0.1876	0.9976	1.0073
city	0.0666	0.1674	0.9942	1.0039
world	0.0532	0.1241	0.9835	0.9931
photography	0.0505	0.1154	1.0000	1.0097
turkish	0.0482	0.1077	0.9872	0.9968
time	0.0452	0.0982	0.9902	0.9999
life	0.0442	0.0950	0.9980	1.0077
visit	0.0424	0.0891	0.9986	1.0083
beautiful	0.0392	0.0787	0.9985	1.0082
bosphorus	0.0354	0.0664	0.9992	1.0089
view	0.0319	0.0550	0.9963	1.0060
street	0.0296	0.0478	0.9990	1.0087
cats	0.0285	0.0442	0.9938	1.0035
europe	0.0285	0.0442	0.9938	1.0035
great	0.0283	0.0436	0.9958	1.0055
hotel	0.0266	0.0380	0.9978	1.0075
trip	0.0263	0.0368	0.9977	1.0075
bluemosque	0.0260	0.0359	1.0000	1.0097
food	0.0259	0.0358	0.9966	1.0063
design	0.0247	0.0316	0.9952	1.0049
turkey, love	0.0246	0.0316	0.9988	1.0085
turkey, city	0.0246	0.0314	0.9988	1.0085
night	0.0236	0.0281	0.9987	1.0085
hagiasophia	0.0233	0.0273	0.9962	1.0059
turkey, photography	0.0225	0.0248	1.0000	1.0097
mosque	0.0221	0.0235	1.0000	1.0097
turkey, turkish	0.0215	0.0214	0.9918	1.0014
amazing	0.0212	0.0206	0.9944	1.0041
turkey, world	0.0208	0.0192	0.9873	0.9969
turkey, visit	0.0198	0.0158	1.0000	1.0097
people	0.0188	0.0127	0.9953	1.0050
happy	0.0185	0.0116	0.9968	1.0065
history	0.0184	0.0115	0.9984	1.0081
music	0.0181	0.0104	1.0000	1.0097
tour	0.0172	0.0076	1.0000	1.0097
summer	0.0171	0.0070	1.0000	1.0097
good	0.0170	0.0069	0.9983	1.0080
turkey, life	0.0170	0.0068	1.0000	1.0097
turkishairlines	0.0170	0.0067	0.9330	0.9421
turkey, bosphorus	0.0168	0.0061	1.0000	1.0097
travel, photography	0.0165	0.0051	1.0000	1.0097
turkey, bluemosque	0.0158	0.0029	1.0000	1.0097
turkey, beautiful	0.0157	0.0025	1.0000	1.0097
business	0.0152	0.0010	0.9827	0.9923
istanbulairport	0.0152	0.0010	0.0619	3.1897
east	0.0151	0.0009	0.9884	0.9980
holiday	0.0149	0.0000	1.0000	1.0097

According to these results, all support values were normalized using the min-max method to give a more significant image of the BCM and to take values between 0-1. Results point out that the lift value takes values close to 1. For this reason, there is no interestingness, but there is an expected co-occurrence.

As shown in Table 2, all the rules show the relationship with Istanbul. This is because each of the tweets in the data set contains the word Istanbul at least one time. There has been no relationship between the other concepts. The strength of associations must be demonstrated according to the values of support. Therefore, the data in Table 2 are listed by support values. The highest support value is between Turkey and Istanbul. With the "travel" association, the support value of "Istanbul" is "0.1323", while the confidence is "0.9943". Accordingly, "travel" and "Istanbul" were used together in 13 percent of all tweets. 'Travel', 'city', 'Turkish', 'visit', 'love', 'photography', 'bosphorus', 'cats', and 'beautiful' are the most common associations. The support value of all words in the dataset except "Turkey" and "travel" is less than 10 percent, but given that the analysis applies to 33,339 tweets, this is quite a big ratio.

Dictionary-based sentiment analysis findings obtained from the association rule analysis revealed whether each tweet was positive, negative or neutral statements. The results obtained from the analysis are illustrated in Table 3 which indicates frequencies for the negative, positive, and neutral tweets, the negative and positive tweet percentages. Results are ranked by decreasing from top to bottom according to the document frequency. Negative tweet percentages point out how many tweets consist of a negative statement. Of the 33,339 tweets in which the word "Istanbul" is used, which makes up the entire data set, 7.46 percent are negative, and 48.21 percent are positive tweets. 44.32 percent of all tweets are neutral statements.

Table 3**.** *Findings of the sentiment analysis*

Associations	Document Frequency	Positive tweet Frequency	Negative tweet Frequency	Neutral tweet Frequency	Percentage of negative tweets	Percentage of positive tweets
Istanbul	33339	16072	2488	14779	7.46	48.21
turkey	10337	4395	1435	4507	13.88	42.52
travel	4478	2337	244	1897	5.45	52.19
city	1858	1265	134	459	7.21	68.08
turkish	1589	844	140	605	8.81	53.12
visit	1426	851	81	471	5.68	59.68
love	1391	1356	20	15	1.44	97.48
photography	1250	786	95	369	7.6	62.88
beautiful	1210	1199	6	5	0.5	99.09
bosphorus	1173	527	27	619	2.3	44.93
cats	962	518	73	371	7.59	53.85
time	921	393	61	575	6.62	42.67
view	905	618	44	415	4.86	68.29
bluemosque	858	373	22	495	2.56	43.47
great	851	838	6	7	0.71	98.47
Istanbulairport	831	266	104	461	11.97	40.33

street	800	319	90	393	11.25	39.88
hotel	799	541	34	224	4.26	67.71
night	776	357	62	357	7.99	46.01
life	759	479	80	250	10.54	63.11
hagiasophia	747	364	83	300	11.11	48.73
tour	714	361	35	318	4.9	50.56
good	705	692	8	5	1.13	98.16
trip	703	463	46	194	6.54	65.86
europe	702	325	64	313	9.12	46.3
amazing	663	660	2	1	0.3	99.55
food	658	328	46	284	6.99	49.85
mosque	655	341	36	278	5.5	52.06
history	610	338	39	233	6.39	55.41
turkishairlines	600	242	70	288	11.67	40.33
people	595	329	98	168	16.47	55.29
happy	526	521	1	4	0.19	99.05
east	516	3	70	216	13.57	44.57
summer	474	265	23	186	4.85	55.91
holiday	469	266	21	182	4.48	56.72
design	462	238	21	203	4.55	51.52
music	455	250	27	178	5.93	54.95
business	407	216	35	156	8,6	53,07

The findings obtained from the association rule mining and sentiment analysis are visualized in a concept map in Figure 4. The dimensions of the nodes indicate the frequency values of the association while the thickness of the lines indicate the support value between the two associations, i.e., the strength of the associations. A triple line between concepts shows a high confidence value, a double line shows a medium confidence value, and single line indicates a low confidence value. The confidence value of all associations is between 98 percent and 100 percent. For this reason, all associations are connected to Istanbul, which is the main brand, with 3 lines. Therefore, confidence values are quite high. The strongest relationship with Istanbul is the concept of "travel" following "Turkey"[2]. This finding is a significant indicator that Istanbul is a tourist city. Since the values of other associations are close to each other, there is no significant difference in line thicknesses in terms of relationship strength. The difference between the frequency of these concepts can also be understood by the size of the circles of the concepts. Since the confidence value in all concepts ranges from 98 percent to 100 percent, all concepts are connected to the main brand with 3 lines. The words "city", "world" and "time" were among the top 10 concepts. The word "city" was used to emphasize that Istanbul is a city. "World" and "time" are associations that add different meanings depending on where they are used. Therefore, it is difficult to say that they are the defining association of Istanbul. For this reason, the concepts of world and time are not included in the map.

[2] Since the word Turkey expresses the country where Istanbul is located, it will negatively affect the interpretation of the brand image on the map (Figure 4). Therefore, Turkey was removed from the map in order to make the map more meaningful.

Table 2 illustrates the relationship of binary concepts such as "Turkey-travel", "Turkey-love", "Turkey-city" and "Turkey-photograph" with Istanbul. Since BCMs show the relationship of a single concept with another concept, these binary associations are not included in the map. Since each tweet included "Istanbul", there was no relationship between the concepts other than Istanbul. In order to see if there is a relationship between concepts other than Istanbul, the word Istanbul was excluded from the data set, analyzed again, and no rules have been formed. No other association has occurred due to words directly related to the concept of Istanbul. If there was an association that indirectly connects to the main brand in this way, the line around words that are not connected to the main brand would be illustrated by a dashed line.

The results of sentiment analysis were also shown in the BCM, revealing the favorability of associations. In Figure 4, as the negativity level of associations increases, the color inside the circles gets darker. As a result of the sentiment analysis, the association in the highest negative expression is the concept of "people" with 16.47 percent. Therefore, the concept of "people" appears to be darker than other associations. On the other hand, 55.29 percent of the concept of people were among positive statements.

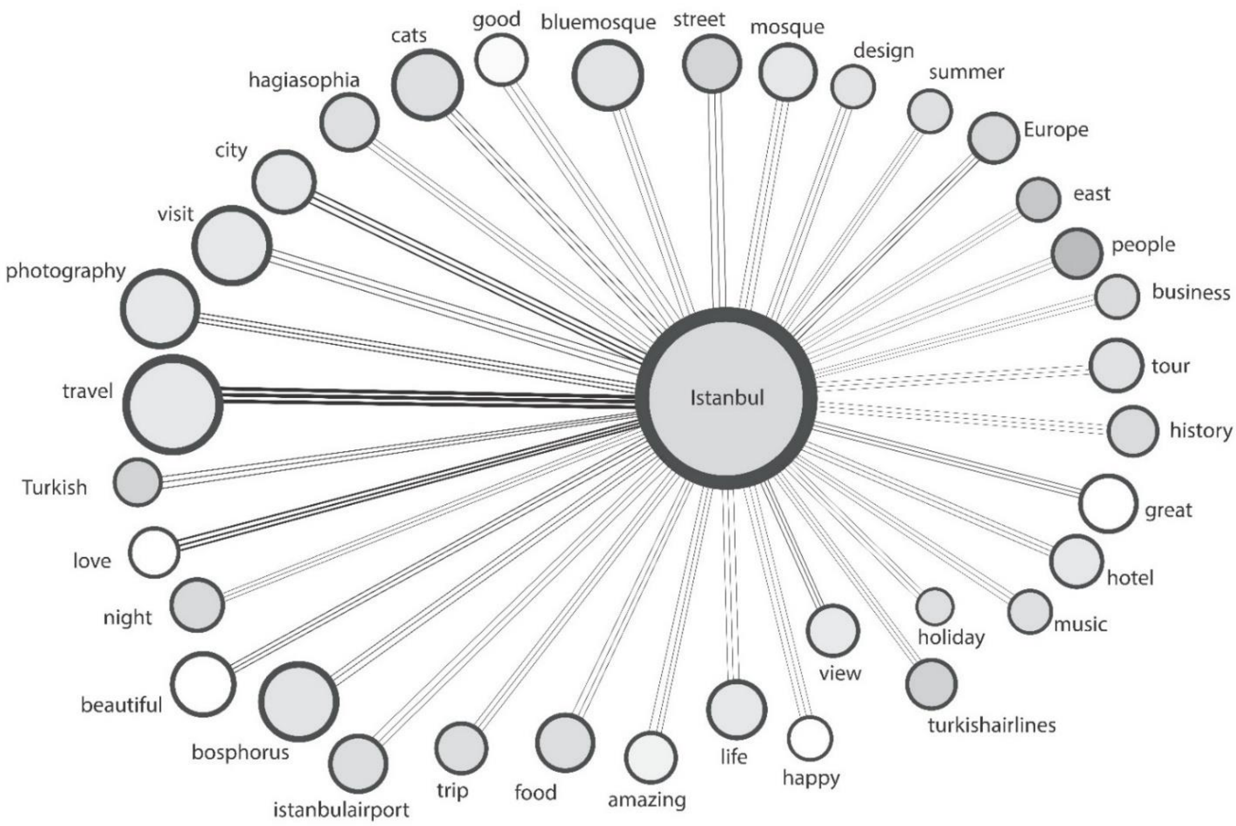

Figure 4. *The Brand Concept Map of Istanbul*

DISCUSSION AND CONCLUSIONS

In the present research, the brand associations of a destination reflected in the eWOM environment are measured and, with the help of data mining, it is indicated how meaningful information is generated from big data. Considering the influence of social media on the formation of destination branding, social media holds a unique position in destination branding research. Thus, thanks to developing data analysis technologies, social media, which was used as a secondary data source in the past, has become the primary data source. One of the most important features of the study is that the data are derived from Twitter. Destination branding practitioners can gain a better insight from research on social media data. Data mining, which many businesses are increasingly using, will also pave the way for these studies to facilitate the analysis.

This study attempted to bring a new perspective to research in this area by using text mining in the BCM to measure associations with the destination brand. BCM method is one of the mixed methods that have the common advantages of quantitative and qualitative methods. In addition, BCM is an effective method of collecting the strength, uniqueness, and favorability of associations in a visual and in revealing the network of associations in the consumer's mind. While previous BCMs were created qualitatively and on a smaller sample, in this study, the favorableness of the associations that make up the brand image and their association strength with the brand were measured and used in a larger sample group. In this context, emotions toward destination associations were determined through in-depth information extraction from the content generated by Twitter users and the connection strength of these associations was analyzed.

This paper showed that favorability dimension can also be measured from Twitter data using sentiment analysis. Text mining allows the unstructured social media data to be configured and to be transformed into significant data. One of the most important advantages of the information obtained from data on social media is that it has a very large volume of sample. Therefore, it paves the way for more reliable results. Today, developing data mining technologies can collect and analyze big data faster.

This paper also showed that unexpected and interesting results can be obtained from big data. For example, the association of "cats" is a very authentic result for Istanbul. The documentary directed by Ceyda Torun in 2016, which tells about Istanbul from the eyes of stray cats, may have played an important role in the formation of these associations. The documentary was defined as “Citizen Kane of Cats” (Kohn, 2020). The most basic result of this study is that Istanbul has a high strength of relationship with “travel”. Therefore, it can be considered that Istanbul is an important tourism destination and is mainly mentioned in terms of tourism on Twitter. However, this result may be because the tweets are in English. If Turkish tweets were collected and analyzed, different findings could be obtained. The associations of 'Travel', 'Visit', 'Trip', 'Tour', and 'Hotel' also indicate that most of the tweets are for tourism. Moreover, findings point out that orientalist elements such as the “Blue Mosque” and “Hagia Sophia” are one of Istanbul's unique tourist attractions. The concept of 'street', one of the strong associations with Istanbul, is also associated with 'photograph'. It suggests that street photographers show interest in Istanbul. The chaotic appearance of the streets of Istanbul is a feature that attracts the attention of photographers. The association of love is among the concepts that have the highest relationship with Istanbul. It is seen that “love” is also used as loving Istanbul in tweets. However, it is difficult to claim that love and romance are unique associations in terms of being able to compete with Paris, Amsterdam, Prague, Venice, and Rome.

Comparison with Previous Studies

In the studies that created the brand association network using text mining, the relationship between concepts was measured by considering word co-occurrence, but in the current study, the relationship between concepts was measured by association rule analysis. In association rule analysis, the degree of concept co-occurrence is represented by the support score. In addition to this parameter, confidence and lift scores are also important elements of the analysis. This study demonstrates the applicability of association rule mining by taking a different approach than previous studies.

Due to the dynamic and changing nature of social media, different results may be obtained from Twitter in different time periods. In this way, it provides an opportunity to observe the changes in the destination associations. For example, while some associations of a travel destination are positive in a time period, negative associations may increase in another time period. Also, if an association has a strong relationship with the destination, the relationship between them may weaken soon. However, it is very difficult and time-consuming to monitor this change in traditional studies measuring destination associations.

Implications for Practitioners

These results will play an important role in determining the content of the messages that will be created in the brand communication projects of Istanbul. The findings can guide the Destination Marketing Organizations. It is estimated that destination brand practitioners will play a key role in creating the messages to be used in brand communication strategies and making effective decisions by seeing which associations they should position their brands with and which associations they should eliminate. Based on the study findings, besides the well-known tourist attractions and the orientalist elements, the hospitality and friendship of the people of Istanbul can be emphasized in the brand communication messages. One of the significant findings of Istanbul is its association with food. It is seen that nearly half of the tweets containing the word "food" are positive tweets. In this context, it shows that food in Istanbul is an important travel motivation that makes it preferable. Thus, it is recommended to include messages about Istanbul culinary culture in promotions.

Future Research and Limitations

In future studies, revealing the brand associations of competing cities abroad simultaneously with Istanbul will allow us to determine the unique brand associations of Istanbul more clearly. This study tried to draw attention to the importance of UGC in destination image research. It will shed light on the development of new methods on the perceptions of the destination image in the online environment and new studies on the use of text mining.

There are some limitations to the study. The most obvious of these are the restrictions imposed by Twitter on the collection of data from this platform. Buying this information from Twitter poses serious costs. For this reason, the data in this study were collected weekly for a year. It is hoped that when this cost is overcome, more effective results will be achieved with larger data. Because of the size of the data, high-performance computers are also needed for data analysis.

The most important limitation of the sentiment analysis method is that it does not perform well in all languages. For example, it has been observed that sentiment dictionaries are not sufficient for Turkish language texts. For this reason, more accurate results can be achieved by applying the machine learning technique. The number of training data will positively affect the accuracy of the results of the sentiment analysis applied with the machine learning technique.

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REFERENCES

Aaker, D. (1991). *Managing Brand Equity*. New York.

Aaker, D. A. (1992). The value of brand equity. *Journal of Business Strategy, 13*(4), 27-32. https://doi.org/10.1108/eb039503

Agrawal, R, Mannila, H., Srikant, R., Toivonen, H., & Verkamo, I. (1996). Fast discovery of association rules. *Advances in knowledge discovery and data mining, 12*(1), 307-328.

Agrawal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. *Proc. of 20th International Conference on Very Large Data Bases, {VLDB'94}* (Vol. 1215, pp. 487-499).

Alaei, A. R., Becken, S., & Stantic, B. (2017). Sentiment analysis in tourism: Capitalizing on big data. *Journal of Travel Research*, *58*(2), 175–191. https://doi.org/10.1177/0047287517747753

Alarcón-Urbistondo, P., Rojas-de-Gracia, M. M., & Casado-Molina, A. (2021). Proposal for employing user-generated content as a data source for measuring tourism destination image. *Journal of Hospitality & Tourism Research*, 10963480211012756. https://doi.org/10.1177/10963480211012756

Alexandris, K., Douka, S., Papadopoulos, P., & Kaltsatou, A. (2008). Testing the role of service quality on the development of brand associations and brand loyalty. *Managing Service Quality*, *18*(3), 239–254. https://doi.org/10.1108/09604520810871865

Alzate, M., Arce-Urriza, M., & Cebollada, J. (2022). Mining the text of online consumer reviews to analyze brand image and brand positioning. *Journal of Retailing and Consumer Services*, *67*, 102989. https://doi.org/10.1016/J.JRETCONSER.2022.102989

Andéhn, M., Kazeminia, A., Lucarelli, A., & Sevin, E. (2014). User-generated place brand equity on Twitter: The dynamics of brand associations in social media. *Place Branding and Public Diplomacy*, *10*(2), 132–144. https://doi.org/10.1057/pb.2014.8

Anderson, J. R., & Bower, G. H. (1980). *Human associative memory*. Psychology Press. https://doi.org/10.2307/1421672

Baloglu, S., & McCleary, K. W. (1999). A model of destination image formation. *Annals of Tourism Research*, *26*(4), 868–897. https://doi.org/10.1016/S0160-7383(99)00030-4

Başfırıncı, Ç. (2016). Analysing brand image through social network analysis: A research on Turkcell and Vodafone brand. *İstanbul Gelişim Üniversitesi Sosyal Bilimler Dergisi*, *3*(2), 25–50.

Becken, S., Alaei, A. R., & Wang, Y. (2020). Benefits and pitfalls of using tweets to assess destination sentiment. *Journal of Hospitality and Tourism Technology*, *11*(1), 19–34. https://doi.org/10.1108/JHTT-09-2017-0090

Bell, R. C. (2005). The repertory grid technique. In F. Fransella (Ed.), *International Handbook of Personal Construct Psychology* (pp. 95–103). John Wiley & Sons Ltd. https://doi.org/10.1002/0470013370.ch9

Bianchi, C., Pike, S., & Lings, I. (2014). Investigating attitudes towards three South American destinations in an emerging long haul market using a model of consumer-based brand equity (CBBE). *Tourism Management*, *42*, 215–223. https://doi.org/10.1016/J.TOURMAN.2013.11.014

Biel, A. (1992). How brand image drives brand equity. *Journal of Advertising Research*, *32*(6), 6-12.

Blanchard, S. J., Aloise, D., & Desarbo, W. S. (2017). Extracting summary piles from sorting task data. *Journal of Marketing Research*, *54*(3), 398–414. https://doi.org/10.1509/jmr.15.0388

Blasi, S., Brigato, L., & Sedita, S. R. (2020). Eco-friendliness and fashion perceptual attributes of fashion brands: An analysis of consumers' perceptions based on twitter data mining. *Journal of Cleaner Production*, *244*, 118701. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.118701

Böger, D., Kottemann, P., Meißner, M., & Decker, R. (2017). A mechanism for aggregating association network data: An application to brand concept maps. *Journal of Business Research, 79*, 90-106. https://doi.org/10.1016/j.jbusres.2017.05.025

Brandt, C., de Mortanges, C. P., Bluemelhuber, C., & van Riel, A. C. R. (2011). Associative networks: A new approach to market segmentation. *International Journal of Market Research, 53*(2), 187-207. https://doi.org/10.2501/ijmr-53-2-187-208

Brandt, C., & de Mortanges, C. P. (2011). City branding: A brand concept map analysis of a university town. *Place Branding and Public Diplomacy, 7*, 50-63. https://doi.org/10.1057/pb.2010.37

Bui, V., Alaei, A. R., Vu, H. Q., Li, G., & Law, R. (2022). Revisiting tourism destination image: A holistic measurement framework using big data. *Journal of Travel Research*, *61*(6), 1287–1307. https://doi.org/10.1177/00472875211024749

Burkhalter, J. N., Wood, N. T., & Tryce, S. A. (2014). Clear, conspicuous, and concise: Disclosures and Twitter word-of-mouth. *Business Horizons*, *57*(3), 319–328. https://doi.org/10.1016/J.BUSHOR.2014.02.001

Cai, L. A. (2002). Cooperative branding for rural destinations. *Annals of Tourism Research*, *29*(3), 720–742. https://doi.org/https://doi.org/10.1016/S0160-7383(01)00080-9

Chen, H. (2012). Dark Web: Exploring and mining the dark side of the web. *2011 European Intelligence and Security Informatics Conference*, Athens, Greece, (pp. 1-2). 10.1109/EISIC.2011.78.

Chen, Y. C. (2017). The relationships between brand association, trust, commitment, and satisfaction of higher education institutions. *International Journal of Educational Management*, *31*(7), 973–985. https://doi.org/10.1108/IJEM-10-2016-0212

Cherfi, H., Napoli, A., & Toussaint, Y. (2003). Towards a text mining methodology using frequent itemsets and association rule extraction. In E. SanJuan (Ed.), *Journées d'informatique Messine - JIM'03* (pp. 285--294). HAL-Inria. https://hal.inria.fr/inria-00107723

Cho, E., Fiore, A. M., & Russell, D. W. (2015). Validation of a fashion brand image scale capturing cognitive, sensory, and affective associations: Testing its role in an extended brand equity model. *Psychology & Marketing*, *32*(1), 28–48. https://doi.org/10.1002/MAR.20762

Choi, S., Jeon, J., Subrata, B., & Kwon, O. (2015). An efficient estimation of place brand image power based on text mining technology. *Journal of Intelligence and Information Systems*, *21*(2), 113–129. https://doi.org/https://doi.org/10.13088/jiis.2015.21.2.113

Christodoulides, G., & de Chernatony, L. (2010). Consumer-based brand equity conceptualisation and measurement: A literature review. *International Journal of Market Research*, *52*(1), 43-66. https://doi.org/10.2501/S1470785310201053

Ci, C., & Choi, S. (2017). How to manage a city's image using the brand concept map and network analysis: A case of Seoul. *Quality and Quantity*, *51*(6), 2441–2456. https://doi.org/10.1007/s11135-016-0402-6

Ciabuca, A. (2015). The development of a semantic differential scale for assessing the perceived image of citizens about Romanian Police Forces. *Procedia - Social and Behavioral Sciences*, *187*, 28–33. https://doi.org/https://doi.org/10.1016/j.sbspro.2015.03.006

Cian, L., & Cervai, S. (2011). The Multi-Sensory Sort (MuSeS). *Qualitative Market Research: An International Journal*, *14*(2), 138–159. https://doi.org/10.1108/13522751111120666

Clarke, H., & Hassanien, A. (2020). An evaluation of Toronto's destination image through tourist generated content on Twitter. *International Journal of Customer Relationship Marketing and Management*, *11*(2), 1–16. https://doi.org/10.4018/IJCRMM.2020040101

Claster, W., Pardo, P., Cooper, M., & Tajeddini, K. (2013). Tourism, travel and tweets: Algorithmic text analysis methodologies in tourism. *Middle East J. of Management*, *1*(1), 81-99. https://doi.org/10.1504/mejm.2013.054071

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, *82*(6), 407–428. https://doi.org/10.1037/0033-295X.82.6.407

Cornwell, T. B., Humphreys, M. S., & Kwon, Y. (2022). Shared brand equity. *Journal of Advertising*, 1-19. https://doi.org/10.1080/00913367.2022.2131656

Culotta, A., & Cutler, J. (2016). Mining brand perceptions from twitter social networks. *Marketing Science, 35*(3), 343-362. https://doi.org/10.1287/mksc.2015.0968

Curlin, T., Jaković, B., & Miloloža, I. (2019). Twitter usage in tourism: Literature review. *Business Systems Research: International Journal of the Society for Advancing Innovation and Research in Economy, 10*(1), 102–119. https://doi.org/10.2478/bsrj-2019-0008

di Pietro, L., di Virgilio, F., & Pantano, E. (2012). Social network for the choice of tourist destination: attitude and behavioural intention. *Journal of Hospitality and Tourism Technology*, *3*(1), 60–76. https://doi.org/10.1108/17579881211206543

Diaz-Garcia, J. A., Ruiz, M. D., & Martin-Bautista, M. J. (2022). A survey on the use of association rules mining techniques in textual social media. *Artificial Intelligence Review, 56*(2), 1175-1200. https://doi.org/10.1007/s10462-022-10196-3

Dillon, W. R., Madden, T. J., Kirmani, A., & Mukherjee, S. (2001). Understanding what's in a brand rating: A model for assessing brand and attribute effects and their relationship to brand equity. *Journal of Marketing Research*, *38*(4), 415–429. https://doi.org/10.1509/jmkr.38.4.415.18910

Dirsehan, T., & Kurtuluş, S. (2018). Measuring brand image using a cognitive approach: Representing brands as a network in the Turkish airline industry. *Journal of Air Transport Management*, *67*, 85–93. https://doi.org/https://doi.org/10.1016/j.jairtraman.2017.11.010

Divakaran, P. K. P., & Xiong, J. (2022). Eliciting brand association networks: A new method using online community data. *Technological Forecasting and Social Change*, *181*, 121769. https://doi.org/https://doi.org/10.1016/j.techfore.2022.121769

Dolnicar, S., Rossiter, J. R., & Grün, B. (2012). 'Pick Any' measures contaminate brand image studies. *International Journal of Market Research*, *54*(6), 821–834. https://doi.org/10.2501/IJMR-54-6-821-834

East, R., Hammond, K., & Lomax, W. (2008). Measuring the impact of positive and negative word of mouth on brand purchase probability. *International Journal of Research in Marketing, 25*(3), 215-224. https://doi.org/10.1016/j.ijresmar.2008.04.001

Elsayed, M., Abdelwahab, A., & Ahdelkader, H. (2019). A proposed framework for improving analysis of big unstructured data in social media. *14th International Conference on Computer Engineering and Systems (ICCES)*, 61–65. https://doi.org/10.1109/ICCES48960.2019.9068154

Feldman, R., & Sanger, J. (2006). *The text mining handbook: Advanced approaches in analyzing unstructured data*. Cambridge: Cambridge University Press. https://doi.org/10.1017/cbo9780511546914

Flores-Ruiz, D., Elizondo-Salto, A., & Barroso-González., M. D. L. O. (2021). Using social media in tourist sentiment analysis: A case study of Andalusia during the Covid-19 Pandemic. *Sustainability*, *13*(7), 1–19.

French, A., & Smith, G. (2013). Measuring brand association strength: A consumer based brand equity approach. *European Journal of Marketing, 47*(8), 1356–1367. https://doi.org/10.1108/03090561311324363

Garay, L. (2019). #Visitspain. Breaking down affective and cognitive attributes in the social media construction of the tourist destination image. *Tourism Management Perspectives*, *32*, 100560. https://doi.org/10.1016/J.TMP.2019.100560

Gartner, W. C. (1994). Image Formation Process. *Journal of Travel & Tourism Marketing*, *2*(2–3), 191–216. https://doi.org/10.1300/J073v02n02_12

Gartner, W. C., & Ruzzier, M. K. (2010). Tourism destination brand equity dimensions: Renewal versus repeat market. *Journal of Travel Research, 50*(5), 471–481. https://doi.org/10.1177/0047287510379157

Gensler, S., Völckner, F., Egger, M., Fischbach, K., & Schoder, D. (2015). Listen to your customers: Insights into brand image using online consumer-generated product reviews. *International Journal of Electronic Commerce, 20*(1), 112-141. https://doi.org/10.1080/10864415.2016.1061792

Goffin, K., Lemke, F., & Koners, U. (2010). Repertory Grid Technique. In *Identifying Hidden Needs: Creating Breakthrough Products* (pp. 125–152). Palgrave Macmillan UK. https://doi.org/10.1057/9780230294486_6

Gorin, A., Nedelko, A., Kosonogov, V., Vakhviyainen, M., Tugin, S., Moiseeva, V., Klucharev, V. & Shestakova, A. (2022). N400 correlate of brand associations. *Journal of Economic Psychology*, *90*, 102506. https://doi.org/https://doi.org/10.1016/j.joep.2022.102506

Han, H., Zhang, J., Yang, J., Shen, Y., & Zhang, Y. (2018). Generate domain-specific sentiment lexicon for review sentiment analysis. *Multimedia Tools and Applications*, *77*(16), 21265–21280. https://doi.org/10.1007/S11042-017-5529-5

Han, J., Kamber, M., & Pei, J. (2012). Data Mining Trends and Research Frontiers. *Data Min*, 585-631.

Hand, D. J. (2007). Principles of data mining. *Drug-Safety*, *30*(7), 621-622.

Henderson, G. R., Iacobucci, D., & Calder, B. J. (1998). Brand diagnostics: Mapping branding effects using consumer associative networks. *European Journal of Operational Research*, *111*(2), 306–327. https://doi.org/10.1016/S0377-2217(98)00151-9

Hodeghatta, U. R., & Sahney, S. (2016). Understanding Twitter as an e-WOM. *Journal of Systems and Information Technology*, *18*(1), 89–115. https://doi.org/10.1108/JSIT-12-2014-0074

Hofstede, A., van Hoof, J., Walenberg, N., & de Jong, M. (2007). Projective techniques for brand image research. *Qualitative Market Research: An International Journal*, *10*(3), 300–309. https://doi.org/10.1108/13522750710754326

Howells, K., & Ertugan, A. (2017). Applying fuzzy logic for sentiment analysis of social media network data in marketing. *Procedia Computer Science*, *120*, 664–670. https://doi.org/10.1016/j.procs.2017.11.293

Hsieh, M. H. (2018). Measuring global brand equity using cross-national survey data. *Journal of International Marketing*, *12*(2), 28–57. https://doi.org/10.1509/JIMK.12.2.28.32897

Huete-Alcocer, N., & Hernandez-Rojas, R. D. (2022). Does local cuisine influence the image of a World Heritage destination and subsequent loyalty to that destination? *International Journal of Gastronomy and Food Science*, *27*, 100470. https://doi.org/10.1016/j.ijgfs.2022.100470

Hussein, N., Alashqur, A., & Sowan, B. (2015). Using the interestingness measure lift to generate association rules. *Journal of Advanced Computer Science & Technology, 4*(1), 156-162. https://doi.org/10.14419/jacst.v4i1.4398

Ibrahim, M. M., & Elborsaly, A. A. (2022). Measuring tourism destination brand equity by using associative networks. *European Journal of Business and Management Research*, *7*(3), 224–235. https://doi.org/10.24018/ejbmr.2022.7.3.1450

Ivanov, S. H., Ilium, S. F., & Liang, Y. (2010). Application of destination brand molecule on destination image and brand perception: An exploratory study. *Tourism*, *58*(4), 339–360. https://doi.org/10.2139/SSRN.1586263

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology, 60*(11), 2169-2188. https://doi.org/10.1002/asi.21149

Jiang, Q., Chan, C.-S., Eichelberger, S., Ma, H., & Pikkemaat, B. (2021). Sentiment analysis of online destination image of Hong Kong held by mainland Chinese tourists. *Current Issues in Tourism*, *24*(17), 2501–2522. https://doi.org/10.1080/13683500.2021.1874312

Jo, T. (2019). *Text mining: Concepts, Implementation, and Big Data Challenge*. Springer, Cham. https://doi.org/10.1007/978-3-319-91815-0

John, D. R., Loken, B., Kim, K., & Monga, A. B. (2006). Brand concept maps: A methodology for identifying brand association networks. *Journal of Marketing Research*, *43*(4), 549-563. https://doi.org/10.1509/jmkr.43.4.549

Karayılmazlar, S., Bardak, T., Avcı, Ö., Kayahan, K., Karayılmazlar, A. S., Çabuk, Y., Kurt, R., & İmren, E. (2019). Determining the orientation in choosing furniture based on social media based on data mining algorithms: Twitter example. *Turkish Journal of Forestry*, *20*(4), 447–457. https://doi.org/10.18182/tjf.609967

Kavaratzis, M. (2004). From city marketing to city branding: Towards a theoretical framework for developing city brands. *Place Branding*, *1*(1), 58–73. https://doi.org/10.1057/PALGRAVE.PB.5990005

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *Journal of Marketing*, *57*(1), 1–22. https://doi.org/10.2307/1252054

Keller, K. L. (2013). *Strategic Brand Management Building, Measuring, and Managing Brand Equity Global Edition* (4th ed.). Pearson.

Kim, D. D. E. (2017). A unified measure of media brand personality: Developing a media brand personality scale for multiple media. *International Journal on Media Management*, *19*(3), 197–221. https://doi.org/10.1080/14241277.2017.1306531

Kim, K., Park, O., Yun, S., & Yun, H. (2017). What makes tourists feel negatively about tourism destinations? Application of hybrid text mining methodology to smart destination management. *Technological Forecasting and Social Change*, *123*, 362–369. https://doi.org/10.1016/j.techfore.2017.01.001

Kiran, P., & Vasantha, S. (2016). Analysing the role of user generated content on consumer purchase intention in the new era of social media and big data. *Indian Journal of Science and Technology*, *9*(43), 1-7. https://doi.org/10.17485/ijst/2016/v9i43/104754

Kladou, S., & Kehagias, J. (2014). Developing a structural brand equity model for cultural destinations. *Journal of Place Management and Development*, *7*(2), 112–125. https://doi.org/10.1108/JPMD-03-2013-0007

Klostermann, J., Plumeyer, A., Böger, D., & Decker, R. (2018). Extracting brand information from social networks: Integrating image, text, and social tagging data. *International Journal of Research in Marketing*, *35*(4), 538-556. https://doi.org/10.1016/j.ijresmar.2018.08.002

Kohn, E. (2020). *"Kedi' is the 'Citizen Kane of Cat Documentaries – Review"*. Indiewire. Retrieved 4 May, 2023, from https://www.indiewire.com/2017/02/kedi-review-cat-documentary-citizen-kane-1201781292/

Koll, O., von Wallpach, S., & Uzelac, B. (2022). Stakeholder-oriented brand management: A Venn-diagram approach to monitor brand associations. *European Management Journal*. https://doi.org/10.1016/j.emj.2022.03.004

Költringer, C., & Dickinger, A. (2015). Analyzing destination branding and image from online sources: A web content mining approach. *Journal of Business Research*, *68*(9), 1836–1843. https://doi.org/10.1016/j.jbusres.2015.01.011

Kumar, C. S. P., & Babu, L. D. D. (2021). Evolving dictionary based sentiment scoring framework for patient authored text. *Evolutionary Intelligence*, *14*(2), 657–667. https://doi.org/10.1007/S12065-020-00366-Z

Lai, K., & Cerpa, N. (2001). Support vs confidence in association rule algorithms. In *Proceedings of the OPTIMA Conference, Curicó* (pp. 1-14).

Leelawat, N., Jariyapongpaiboon, S., Promjun, A., Boonyarak, S., Saengtabtim, K., Laosunthara, A., Yudha, A. K., & Tang, J. (2022). Twitter data sentiment analysis of tourism in Thailand during the COVID-19 pandemic using machine learning. *Heliyon*, *8*(10), e10894. https://doi.org/10.1016/J.HELIYON.2022.E10894

Lim, K., & O'Cass, A. (2001). Consumer brand classifications: an assessment of culture-of-origin versus country-of-origin. *Journal of Product & Brand Management*, *10*(2), 120–136. https://doi.org/10.1108/10610420110388672

Liu, B. (2010). Sentiment analysis and subjectivity. In *Handbook of Natural Language Processing* (2. Ed.) (pp. 627-666).

Liu, B., & Zhang, L. (2012). A survey of opinion mining and sentiment analysis. In *Mining Text Data* (pp. 415-463). Springer, Boston, MA. https://doi.org/10.1007/978-1-4614-3223-4_13

Liu, M. T., Liu, Y., Mo, Z., & Ng, K. L. (2021). Using text mining to track changes in travel destination image: the case of Macau. *Asia Pacific Journal of Marketing and Logistics*, *33*(2), 371–393. https://doi.org/10.1108/APJML-08-2019-0477

Liu, X., Burns, A. C., & Hou, Y. (2017). An investigation of brand-related user-generated content on Twitter. *Journal of Advertising*, *46*(2), 236–247. https://doi.org/10.1080/00913367.2017.1297273

Lopes, A. A., Pinho, R., Paulovich, F., & Minghim, R. (2007). Visual text mining using association rules. *Computers & Graphics*, *31*(3), 316–326. https://doi.org/10.1016/j.cag.2007.01.023

Lopez, A., Guerra, E., Gonzalez, B., & Madero, S. (2020). Consumer sentiments toward brands: the interaction effect between brand personality and sentiments on electronic word of mouth. *Journal of Marketing Analytics*, *8*(4), 203–223. https://doi.org/10.1057/S41270-020-00085-5/FIGURES/8

Low, G. S., & Lamb, C. W. Jr. (2000). The measurement and dimensionality of brand associations. *Journal of Product & Brand Management*, *9*(6), 350–370.

Mak, A. H. N. (2017). Online destination image: Comparing national tourism organisation's and tourists' perspectives. *Tourism Management*, *60*, 280–297. https://doi.org/10.1016/j.tourman.2016.12.012

Marchand, A., Hennig-Thurau, T., & Wiertz, C. (2017). Not all digital word of mouth is created equal: Understanding the respective impact of consumer reviews and microblogs on new product success. *International Journal of Research in Marketing*, *34*(2), 336–354. https://doi.org/10.1016/J.IJRESMAR.2016.09.003

Marine-Roig, E., & Anton Clavé, S. (2015). Tourism analytics with massive user-generated content: A case study of Barcelona. *Journal of Destination Marketing & Management*, *4*(3), 162–172. https://doi.org/10.1016/J.JDMM.2015.06.004

Matheson, J. L., & McCollum, E. E. (2008). Using metaphors to explore the experiences of powerlessness among women in 12-step recovery. *Substance Use and Misuse*, *43*(8-9), 1027-1044. https://doi.org/10.1080/10826080801914287

McNicholas, P. D., Murphy, T. B., & O'Regan, M. (2008). Standardising the lift of an association rule. *Computational Statistics and Data Analysis*, *52*(10), 4712-4721. https://doi.org/10.1016/j.csda.2008.03.013

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Miner, G. D., Elder, J., & Nisbet, R. A. (2012). Practical text mining and statistical analysis for non-structured text data applications. In *Practical Text Mining and Statistical Analysis for Non-structured Text Data Applications*. Elsevier Inc. https://doi.org/10.1016/C2010-0-66188-8

Mishra, M. S., & Sharma, R. W. (2019). Brand crisis-sentiment analysis of user-generated comments about @Maggi on Facebook. *Corporate Reputation Review*, *22*(2), 48–60. https://doi.org/10.1057/s41299-018-0057-4

Mitra, S., & Jenamani, M. (2020). OBIM: A computational model to estimate brand image from online consumer review. *Journal of Business Research*, *114*, 213–226. https://doi.org/10.1016/J.JBUSRES.2020.04.003

Nadeau, J., Wardley, L. J., & Rajabi, E. (2021). Tourism destination image resiliency during a pandemic as portrayed through emotions on Twitter. *Tourism and Hospitality Research*, *22*(1), 60–70. https://doi.org/10.1177/14673584211038317

Nam, H., Joshi, Y., & Kannan, P. K. (2017). Harvesting brand information from social tags. *Journal of Marketing*, *81*(4), 88–108. https://doi.org/10.1509/jm.16.0044

Nautiyal, R., Albrecht, J. N., & Carr, A. (2022). Can destination image be ascertained from social media? An examination of Twitter hashtags. *Tourism and Hospitality Research*. https://doi.org/10.1177/14673584221119380

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science*, *31*(3), 521-543. https://doi.org/10.1287/mksc.1120.0713

Nielsen, F. Å. (2011). A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. *CEUR Workshop Proceedings*.

Oliverio, J. (2018). A survey of social media, big data, data mining, and analytics. *Journal of Industrial Integration and Management*, *3*(03), 1850003. https://doi.org/10.1142/S2424862218500033

Osgood, C. E. (1959). The representational model and relevant research methods. In I. Pool (Ed.), *Trends in Content Analysis* (pp. 33–38). Illinois Press.

Özyirmidokuz, E. K. (2014). Mining unstructured Turkish economy news articles. *Procedia Economics and Finance*, *16*, 320-328. https://doi.org/10.1016/s2212-5671(14)00809-0

Paolanti, M., Mancini, A., Frontoni, E., Felicetti, A., Marinelli, L., Marcheggiani, E., & Pierdicca, R. (2021). Tourism destination management using sentiment analysis and geo-location information: A deep learning approach. *Information Technology & Tourism*, *23*(2), 241–264. https://doi.org/10.1007/s40558-021-00196-4

Park, J., Yang, D., & Kim, H. Y. (2023). Text mining-based four-step framework for smart speaker product improvement and sales planning. *Journal of Retailing and Consumer Services*, *71*, 103186. https://doi.org/10.1016/J.JRETCONSER.2022.103186

Park, S. B., Kim, J., Lee, Y. K., & Ok, C. M. (2020). Visualizing theme park visitors' emotions using social media analytics and geospatial analytics. *Tourism Management*, *80*, 104127. https://doi.org/10.1016/J.TOURMAN.2020.104127

Perez Cabañero, C., Bigne, E., Ruiz Mafe, C., & Cuenca, A. C. (2020). *Sentiment Analysis of Twitter in Tourism Destinations*, 1–3. https://doi.org/10.4995/carma2020.2020.11621

Phong, L. T., Nga, T. H., Hanh, N. T., & van Minh, N. (2020). Relationship between brand association and customer loyalty: The case of online retail industry. *Management Science Letters*, *10*(7), 1543–1552. https://doi.org/10.5267/j.msl.2019.12.012

Pich, C., Armannsdottir, G., & Dean, D. (2015). The elicitation capabilities of qualitative projective techniques in political brand image research. *International Journal of Market Research*, *57*(3), 357–394. https://doi.org/10.2501/IJMR-2015-033

Pike, S. (2009). Destination brand positions of a competitive set of near-home destinations. *Tourism Management*, *30*(6), 857–866. https://doi.org/10.1016/J.TOURMAN.2008.12.007

Plumeyer, A., Kottemann, P., Böger, D., & Decker, R. (2019). Measuring brand image: A systematic review, practical guidance, and future research directions. *Review of Managerial Science, 13,* 227-265. https://doi.org/10.1007/s11846-017-0251-2

Qu, H., Kim, L. H., & Im, H. H. (2011). A model of destination branding: Integrating the concepts of the branding and destination image. *Tourism Management*, *32*(3), 465–476. https://doi.org/10.1016/J.TOURMAN.2010.03.014

Rahman, K., & Areni, C. S. (2016). The benefits of quantifying qualitative brand data: A mixed-method approach for converting free brand associations to a brand equity index. *International Journal of Market Research*, *58*(3), 421–450. https://doi.org/10.2501/IJMR-2015-053

Rajman, M., & Besançon, R. (1998). Text Mining: Natural Language techniques and Text Mining applications BT - Data Mining and Reverse Engineering: Searching for semantics. In S. Spaccapietra & F. Maryanski (Eds.), *IFIP TC2 WG2.6 IFIP Seventh Conference on Database Semantics (DS-7) 7–10 October 1997, Leysin, Switzerland* (pp. 50–64). Springer US. https://doi.org/10.1007/978-0-387-35300-5_3

Ren, G., & Hong, T. (2017). Investigating online destination images using a topic-based sentiment analysis approach. *Sustainability, 9*(10), 1765. https://doi.org/10.3390/su9101765

Romaniuk, J. (2014). Comparing methods of measuring brand personality traits. *Journal of Marketing Theory and Practice*, *16*(2), 153–161. https://doi.org/10.2753/MTP1069-6679160205

Sahin, S., & Baloglu, S. (2011). Brand personality and destination image of Istanbul. *Anatolia*, *22*(1), 69–88. https://doi.org/10.1080/13032917.2011.556222

Schnittka, O., Sattler, H., & Zenker, S. (2012). Advanced brand concept maps: A new approach for evaluating the favorability of brand association networks. *International Journal of Research in Marketing*, *29*(3), 265–274. https://doi.org/10.1016/j.ijresmar.2012.04.002

Shams, R., Alpert, F. & Brown, M. (2015). Consumer perceived brand innovativeness. *European Journal of Marketing*, *49*(9/10), 1589–1615. https://doi.org/10.1108/EJM-05-2013-0240

Shimada, K., Inoue, S., Maeda, H., & Endo, T. (2011). Analyzing tourism information on Twitter for a local city. *2011 First ACIS International Symposium on Software and Network Engineering*, 61–66. https://doi.org/10.1109/SSNE.2011.27

Spry, L., & Pich, C. (2021). Enhancing data collection methods with qualitative projective techniques in the exploration of a university's brand identity and brand image. *International Journal of Market Research*, *63*(2), 177–200. https://doi.org/10.1177/1470785320943045

Statista. (2020). *Largest cities in Europe in 2020*. https://www.statista.com/statistics/1101883/largest-european-cities/.

Stepchenkova, S., & Li, X. (Robert). (2014). Destination image: Do top-of-mind associations say it all? *Annals of Tourism Research*, *45*, 46–62. https://doi.org/10.1016/j.annals.2013.12.004

Surugiu, C., Tudorache, D. M., Aștefănoaiei, R. M., & Surugiu, M. R. (2021). Bucharest cultural heritage through the eyes of social media users. *Anatolia*, *33*(4), 576-587. https://doi.org/10.1080/13032917.2021.1984960

Tan, P. N., Steinbach, M., & Karpatne, K. (2018). Association analysis: Basic concepts and algorithms. In P.-N. Tan, M. Steinbach, A. Karpatne & V. Kumar (Eds.), *Introduction to Data Mining* (2nd ed., pp. 357–449). https://www-users.cs.umn.edu/~kumar001/dmbook/ch5_association_analysis.pdf

Teichert, T. A., & Schöntag, K. (2010). Exploring consumer knowledge structures using associative network analysis. *Psychology and Marketing*, *27*(4), 369-398. https://doi.org/10.1002/mar.20332

Tseng, C., Wu, B., Morrison, A. M., Zhang, J., & Chen, Y. (2015). Travel blogs on China as a destination image formation agent: A qualitative analysis using Leximancer. *Tourism Management*, *46*, 347–358. https://doi.org/10.1016/j.tourman.2014.07.012

Viñán-Ludeña, M. S., & de Campos, L. M. (2022). Discovering a tourism destination with social media data: BERT-based sentiment analysis. *Journal of Hospitality and Tourism Technology*, *13*(5), 907–921. https://doi.org/10.1108/JHTT-09-2021-0259

Vriens, M., Chen, S., & Schomaker, J. (2019). The evaluation of a brand association density metric. *Journal of Product and Brand Management*, *28*(1), 104–116. https://doi.org/10.1108/JPBM-02-2018-1768

Wong, C. U. I., & Qi, S. (2017). Tracking the evolution of a destination's image by text-mining online reviews - the case of Macau. *Tourism Management Perspectives*, *23*, 19–29. https://doi.org/10.1016/J.TMP.2017.03.009

Wong, P. C., Whitney, P., & Thomas, J. (1999). Visualizing association rules for text mining. *Proceedings of the IEEE Symposium on Information Visualization*. https://doi.org/10.1109/infvis.1999.801866

Yan, H., Ma, M., Wu, Y., Fan, H., & Dong, C. (2022). Overview and analysis of the text mining applications in the construction industry. *Heliyon*, *8*(12), e12088. https://doi.org/10.1016/J.HELIYON.2022.E12088

Yan, Y., Chen, J., & Wang, Z. (2020). Mining public sentiments and perspectives from geotagged social media data for appraising the post-earthquake recovery of tourism destinations. *Applied Geography*, *123*, 102306. https://doi.org/10.1016/J.APGEOG.2020.102306

Yang, F. X., Li, X., & Choe, Y. (2022). What constitutes a favorable destination brand portfolio? Through the lens of coherence. *Tourism Management*, *90*, 104480. https://doi.org/10.1016/j.tourman.2021.104480

Zaltman, G. (1995). *Metaphor elicitation method and apparatus* (Patent No. 5,436,830).

Zenker, S. (2014). Measuring place brand equity with the advanced Brand Concept Map (aBCM) method. *Place Branding and Public Diplomacy, 10,* 158-166. https://doi.org/10.1057/pb.2014.2

Zenker, S., & Braun, E. (2015). Rethinking the measurement of place brands. In K. Mihalis, G. Warnaby & G. J. Ashworth (Eds.), *Rethinking Place Branding Comprehensive: Brand Development for Cities and Regions* (pp. 211–224). Springer, Cham. https://doi.org/10.1007/978-3-319-12424-7

Zenker, S., & Braun, E. (2017). Questioning a "one size fits all" city brand: Developing a branded house strategy for place brand management. *Journal of Place Management and Development*, *10*(3), 270–287. https://doi.org/10.1108/JPMD-04-2016-0018

Zhang, Y., Chen, M., & Liu, L. (2015). A review on text mining. *2015 6th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, 681–685. https://doi.org/10.1109/ICSESS.2015.7339149

Zhang, Z., Luo, M., Luo, Z. & Niu, H. (2022). The international city image of Beijing: A quantitative analysis based on twitter texts from 2017–2021. *Sustainability (Switzerland)*, *14*(17), 10675. https://doi.org/10.3390/su141710675

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INVESTIGATION OF ANTECEDENTS AND CONSEQUENCES OF USEFULNESS IN ONLINE TRAVEL COMMUNITIES: THE MODERATING ROLE OF DECISION MAKING STAGE

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ABSTRACT

This study examines the perceived usefulness (PU) of online discourse and the decision-making behavior of users in Online Travel Communities (OTCs). Partial least squares structural equation modeling (PLS-SEM) was used on secondary data available in OTCs in the form of 852 threads to empirically test the proposed integrated model. The antecedents of the perceived usefulness of online travel communities were found to be the argument quality and credibility. These influence the PU of user-generated content significantly and are helpful in information adoption in OTCs. The PU of OTC discourse positively impacts travelers' information adoption and decision-making. The current study offers implications for OTCs and online service providers for enhancing the usefulness of user-generated content in OTCs and social media sites, leading to online information use and travel decision-making. Prior literature has explored the nature and magnitude of the influence of electronic word-of-mouth (eWOM) on information adoption and intention to use information for travel purchases from users' perspectives and has investigated the PU of third-party travel sites. This paper is an effort to examine PU and decision-making by analyzing the User-Generated-Content (UGC) posted by the actual users.

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INTRODUCTION

Developments in internet technologies have amplified social networking sites and mobile applications that have helped in the extensive spread of electronic word-of-mouth (eWOM) in tourism information systems (Capriello et al., 2013; Gvili & Levy, 2016). eWOM can be available in the online sites' records, which can be retrieved anywhere, anytime, distinct from the offline word of mouth (Yang et al., 2012). The growth of eWOM in the tourism industry has augmented the expansion and popularity of third-party travel sites, which offer a platform for interactions among users and generate User-Generated-Content (UGC) about travel and service providers (Chong et al., 2018). Tilly et al. (2015) stated that around 20 to 45% of travelers use social media (SM) for information searching, alternative evaluation, and travel planning; however, only 5 to 30% of users utilize social media to share their experiences online. The generation of eWOM takes place on social media sites and online review sites as consumers post opinions and views, and consumers use suggestions or recommendations available in the form of eWOM to support their decisions (Munar & Jacobsen, 2014). Social networking sites and Online Travel Communities (OTCs) help facilitate travelers' travel decisions and evaluate their experiences while sharing knowledge online with potential travelers (Hajli et al., 2018; Kim et al., 2013). The information writing and posting on social media sites is the "giving" process, while the "taking" process of information search involves the interaction process where the available information is selected, read, replied to, and liked. The "taking" process has been investigated less than the former (Chung et al., 2015). The activities of liking, commenting on posts, and replying to any remark enhance the intimacy among social media users (Chung et al., 2015). Information in OTCs is co-created through prosumption as information is created and shared by residents, potential tourists, and businesses on a single platform (Oriade & Robinson, 2019). In OTCs, copious thoughts and ideas are exchanged on a single platform in the form of thread postings that also build the content quality of OTCs (Brand, 2016). The threads having longer content posted by users facilitate the Original Poster (OP) in decision making by offering detailed information, sharing observations, and providing guidance and suggestions while reducing uncertainty (Fang et al., 2018). Information usefulness in online communities depends on the trustworthiness, completeness, and timeliness of information, positively influencing users' purchase intentions (Cheung, 2014). The researchers have developed conceptual models to elaborate on the use of eWOM in travel decisions (Papathanassis & Knolle, 2011; Ayeh et al., 2013; Chong et al., 2018; Wang

& Li, 2019). Chong et al. (2018) have categorized the previous research on eWOM in tourism from the perspective of the sender, tourism managers, third parties, and the eWOM users. However, the studies have explored the nature and magnitude of eWOM influence on travelers' intentions to adopt and use to finalize their plans (Cheung, 2014; Chung et al., 2015; Chong et al., 2018), but these studies have disclosed the implications from the perspective of the users.

This paper investigates which aspects of online postings influence UGC's usefulness and what makes the Original Poster (OP) adopt the information shared by fellow members and make their final travel decisions. Additionally, the studies have analyzed respondent characteristics such as gender (Chong et al., 2018; Dedeoglu, 2019) and social presence (Chung et al., 2015), but the users' need for information to make final travel decisions has not been studied yet. Two stages of decision making, information search and alternative evaluation, are measured as moderators for the current study. Information search behavior in OTCs was analyzed by investigating the giving and taking process of the community members, and the authors have analyzed the UGC posted by the actual users and examined the real data produced by them. As in OTCs, the members communicate with each other for information search and travel planning purposes, and this study evaluates online discourse in OTCs using an Elaborate Likelihood Model (ELM) for measuring the impact of credibility (peripheral) and argument quality (central) on travel adoption by analyzing the mediating effect of perceived usefulness and also explores the decision-making of users.

The paper has the following structure. First of all, in the literature review, the antecedents of Perceived Usefulness are elaborated according to the ELM. Then information adoption and decision-making in OTCs are explained, along with the proposed hypotheses. Further, the research model is explained. Next, the research methodology and data collection procedure are elaborated. Subsequently, the data analysis carried out in Smart PLS is explained. Finally, the research findings are elucidated along with the implications.

LITERATURE REVIEW

Information Adoption Model

Elaborate Likelihood Model (ELM) has been a popular mechanism for understanding the information adoption behavior of eWOM users as it offers insights into how users get influenced by the available information (Filieri & McLeay, 2014; Cheung et al., 2008). An ELM examines the users' attitudes influenced by peripheral and central routes defined by their cognitive process (Chong et al., 2018). The users taking the central route for the information process think critically and analyze the possible cues related to the arguments decisively and then form an attitude about the particular service (Zhou, 2017; Owusu et al., 2016; Sher & Lee, 2009). The level of argument, measured by a person perceiving it as strong or weak, defines the argument quality (Petty & Cacioppo, 1986), which is analyzed using the central route.

On the other hand, a user taking a peripheral route for forming an attitude does not look for the quality of argument in the information offered but searches for the environmental cues that support the decision (Sussman & Siegal, 2003). Conclusions are drawn from the heuristic indicators presented in the online information, evaluated by adopting the peripheral route (Chung et al., 2015). The peripheral route evaluates source credibility (Chong et al., 2018; Wang & Li, 2019), where efforts are not made to message elaboration (Angst & Agarwal, 2009). The argument quality and credibility of UGC stimulate a positive and significant influence on information adoption as per the ELM (Sussman & Siegal, 2003; Chan & Ngai, 2011).

With the support of the previous findings, this study proposes that an ELM can be utilized to understand the information adoption behavior of OTC members. Also, information giving has been the main focus for recognizing the community characteristics of users' motivation (Lee et al., 2014), while information sharing is the primary role OTCs play by enabling users to post queries, replies, and sharing diverse information on travel which need investigation (Chung et al., 2015). Similar to Sussman and Siegal (2003), Chung et al. (2015), and Chong et al. (2018), the argument quality of OTC posts has been taken by way of a central influence, and information credibility has been examined as a peripheral influence in this study.

Hypothesized Model

Hypotheses (H1–11) have been formulated according to the following categories:

Argument Quality

The influential strength of the argument presented in the online content shared by users defines the argument quality (Bhattacherjee & Sanford, 2006). Strong arguments motivate the users to participate in information activities with a strong attitude, and they tend to evaluate information critically (Li, 2013). Chong et al. (2018) have examined argument quality in terms of the review accuracy, argument strength, timeliness, sidedness, review framing, completeness, relevance, and certainty shown in online travel reviews. McKinney et al. (2002) have investigated argument quality as information accuracy, content, timeliness, and structure. Chung et al. (2015) analyzed the completeness, accuracy, consistency, timeliness, and definite travel information shared on social media to understand travelers' information adoption behavior. Further, the argument quality and information usefulness have been significantly addressed in the domain of social media, Facebook, online communities, and computer-mediated communication research (e.g., Chung et al., 2015; Chong et al., 2018; Wang & Li, 2019; Bhattacherjee & Sanford 2006; Li, 2013) and found significant association between the two constructs. The argument quality of online travel information available on social media influences the perceived usefulness and motivates to adopt the information shared (Chung et al., 2015). In OTCs, members write answers to a query posted by an information seeker, and the various replies share diverse knowledge with varying quality. The original poster evaluates the replies according to the need. The messages with strong arguments are likely to be useful for the OP to reply to and motivate them to adopt the information for travel decision-making. Thus, the following hypotheses have been formulated:

H1a: *Argument Quality of OTC posts positively influences the online discourse's Perceived Usefulness.*

H1b: *Argument Quality of OTC posts positively influences online Information Adoption.*

Credibility

The trustworthiness, believability, and reliability of information provided on online travel platforms define its credibility for travelers (Tormala & Petty, 2004; Cheung et al., 2009) and have been assessed based on the content offered as eWOM irrespective of the trustworthiness of the information provider or the social networking site (Cheung et al., 2009; Xie & Boush, 2011). Source credibility influences PU as well as social relationships, which further augment the information adoption from UGC in social media (Chung et al., 2015). Reviews' sources, expertise, trustworthiness, rating, and consistency have been examined to evaluate the credibility of travel reviews by Chong et al. (2018). The online travel reviews (OTRs) posted by numerous reviewers are measured as credible when there is consistency among the statements and views shared (Chong et al., 2018). Previous research has investigated the source credibility by analyzing the profile of the repliers, or authors, such as the original name, number of posts, number of replies (Chen & Ku 2012), and the expertise, trustworthiness, and knowledge of the person who shares the information (Dedeoglu, 2019) but the credibility of the information content needs to be investigated to judge the reliability and trustworthiness. Chong et al. (2018) have investigated credibility by analyzing the consistency and trustworthiness of the eWOM in an online review site and found it influential in eWOM usefulness.

Likewise, the information shared in OTC threads may contain unclear or rational information, and the content should be assessed to investigate the consistency and justification in the various posts written by many repliers in the threads. It has been hypothesized that more credible information leads to high perceived usefulness and motivates information adoption. We propose the following:

H2a: *The credibility of OTC posts positively influences the online discourse's Perceived Usefulness.*

H2b: *The credibility of OTC posts has a positive influence on online Information Adoption.*

Perceived Usefulness

Perceived Usefulness (PU) is now being examined in the travel and tourism area, where many researchers have explored the PU of Information Systems (IS). Scholars have investigated the determinants of PU information systems and technology and found information quality, system quality, and infrastructures as major determents of PU (Alsabawy et al., 2016) along with individual and situational factors (Agarwal & Karahanna, 2000) and the depth and length of online reviews (Hu et al., 2016). Wang and Li (2019) studied the utilitarian perception of reviewers by evaluating the quality of OTRs, which has a positive relationship with the PU of travel review sites and the online community (Park et al., 2014). Perceived usefulness influences Facebook users' behavior (Yang & Brown, 2015), and it positively affects consumers' trust in review sites besides influencing their purchase intentions (Agag & El-Masry, 2017). Also, PU has been found influential in users' continuous use of online travel services and encourages them to recommend the tourism services to others (Li & Liu, 2014).

In OTCs, members post queries to seek information to help them plan and sort out travel issues. However, the given information in the OTCs is written by many repliers, and it becomes decisive to ensure that the OP gets useful information. The information provided by community members needs to be applicable in the specific situation to solve the issue at hand. The information seeker can decide whether to adopt the information provided or make the travel decision by evaluating the usefulness of the shared knowledge. Thus, it is anticipated that:

H3a: *Perceived Usefulness of OTC posts influences online Information Adoption positively.*

The Mediating Role of Perceived Usefulness

Chung et al. (2015) have investigated the SM users' perception and disclosed that the argument and credibility of online information positively influence the information usefulness, which further influences social relationships significantly. In OTCs, the OP expects to get context-specific information, which can be applied in an actual situation. They are not likely to focus on the undesired and impractical knowledge shared by the community members. Users most commonly prefer positive and negative evaluations for information support in forums (Savolainen, 2014). Again, despite numerous answers from various members of OTC, people prefer short and diverse answers that enhance the information utility for travel planning (Gal-Tzur et al., 2020). The usefulness of information mediates the effect of eWOM quantity, credibility, and quality on users' purchase decisions (Matute et al., 2016) and significantly affects travel planning (Mendes et al., 2018). Thus, it is assumed that the higher the PU of OTC information, the more likely users are to adopt the information. Tourists get influenced by the usefulness of the information, besides giving weightage to the argument's quality and credibility. It can be hypothesized that PU will significantly affect the influence of argument quality and credibility on information adoption by OTC users.

H3b: *Perceived Usefulness of OTC posts mediates the influence of Argument Quality on Information Adoption.*

H3c: *Perceived Usefulness of OTC posts mediates the influence of Credibility on Information Adoption.*

The Mediating Role of Perceived Usefulness

Sussman and Siegal (2003) have demarcated the information adoption by how users accept and use the information provided for a particular case. Cheung et al. (2008) have found information helpfulness a significant determinant for information adoption in a virtual cuisine community. Filieri and McLeay (2014) disclosed that the timeliness, accuracy, value added, and relevancy of online travel reviews and the product ranking significantly influence information adoption by travelers. Cheung (2014) surveyed online customer community members to explore the relationships regarding eWOM information adoption and concluded that reliability, timeliness, completeness, and quality positively influence the information usefulness, and that usefulness impacts the purchase intentions of the community members. Purchase decisions are the decisions of consumers to buy or not a particular product or service after reading user-generated content on travel eWOM sites (Wang & Li, 2019). For purchase decisions, eWOM has been found to be the most significant source of information (Litvin et al., 2008). Users are more likely to accept the information that can be applied in a specific situation and help make decisions. Wang and Li (2019) have proposed that a multi-purpose–oriented design of a travel review site would positively influence the perceived usefulness, further stimulating the eWOM use and generation positively, enabling users to make purchase decisions.

In OTCs, the members participate in the online discourse and discuss various travel issues. The original poster must write comments on the knowledge shared by fellow members to call a thread complete. Only the OP's comments on the replies provide the direction to the discussion and lead it to a conclusion. Thus, the positive reply to the following posts indicates the agreement and intention to adopt the information. A high number of posts by the OP also indicates high involvement. The OTC members show indications of adopting information by interacting more with users who offer useful information. High intentions to adopt the offered suggestions and recommendations will influence travel decisions by generating more useful discourse. The user-generated content tells whether the OP intends to adopt some part of the information or is likely to take the travel decision. Also, the OP mentions the travel decisions in the replies. Hence, we can expect that:

H4a: *Perceived Usefulness of OTC posts is positively associated with travel Decision Making.*

H4b: *Information Adoption of OTC posts is positively associated with travel Decision Making.*

H4c: *Information Adoption mediates the relationship between Perceived Usefulness and travel Decision Making.*

Decision Making Phases as Moderator Analysis

Li et al. (2019) compared the high-quality answers for "information-seeking questions and discussion-seeking questions" in Research Gate Q&A, an online community used by academicians worldwide. The authors have revealed significant differences between the high-quality answers for the two categories; for instance, the theoretical basis was essential for information-seeking questions, and the replies' authority was a significant element for the discussion-seeking questions. However, Li et al. (2020) did not find significant differences in the scholars' perceptions of quality criteria across the two question types.

The Tourists' Cognitive Decision Making (TCDM) model proposed by Chen (1998) has stressed the cognitive process of travel decision-making, including the Problem Formulation stage, Information Search, Alternative Evaluation, and Implementation as decision-making stages. Twumasi and Adu-Gyamfi (2013), in the study of TripAdvisor, revealed that tourists actively use the OTC for disclosing their travel needs, information search, alternate evaluation, and final decisions. Gretzel et al. (2007) also found that travelers analyze reviews for idea generation, option evaluation, and confirming their final choices. The queries seeking "Information Search" and "Alternatives Evaluation" have different motives behind their postings in OTCs. As alternative evaluation is the second stage of travel decision-making, it is assumed that tourists posting such queries have basic knowledge about the topic or issue, and they are keener on others' opinions and recommendations. Thus, the argument quality can be important for these enquirers.

On the contrary, people post simple queries to get information about travel planning and facilities, and repliers answer such queries more objectively by sharing factual information, details, and general knowledge. Chung et al. (2015) analyzed the moderating effect of social presence on argument quality and source credibility influence on the PU of travel information. The results signified that in low social presence, argument quality is more significant on PU while the consequences of source credibility are more significant for PU. Choudhary and Gangotia (2017) revealed that Generation Y travelers use social networking sites actively to get clarity about various alternatives and make travel decisions. Thus, the two stages of travel decision-making have been used as the moderators in the proposed research model, and the following hypotheses are proposed:

H5: *The Argument Quality of online discourse influences PU differently for travel decision-making stages.*

H6: *The Argument Quality of online discourse influences Information Adoption differently for travel decision-making stages.*

H7: *The Credibility of online discourse influences Information Adoption differently for travel decision-making stages.*

H8: *The Credibility of online discourse influences PU differently for travel decision-making stages.*

H9: *The Perceived Usefulness of online discourse influences Information Adoption differently for travel decision-making stages.*

H10: *The Perceived Usefulness of online discourse influences Decision-making differently for travel decision-making stages.*

H11: *The Information Adoption of online discourse influences Decision-making differently for travel decision-making stages.*

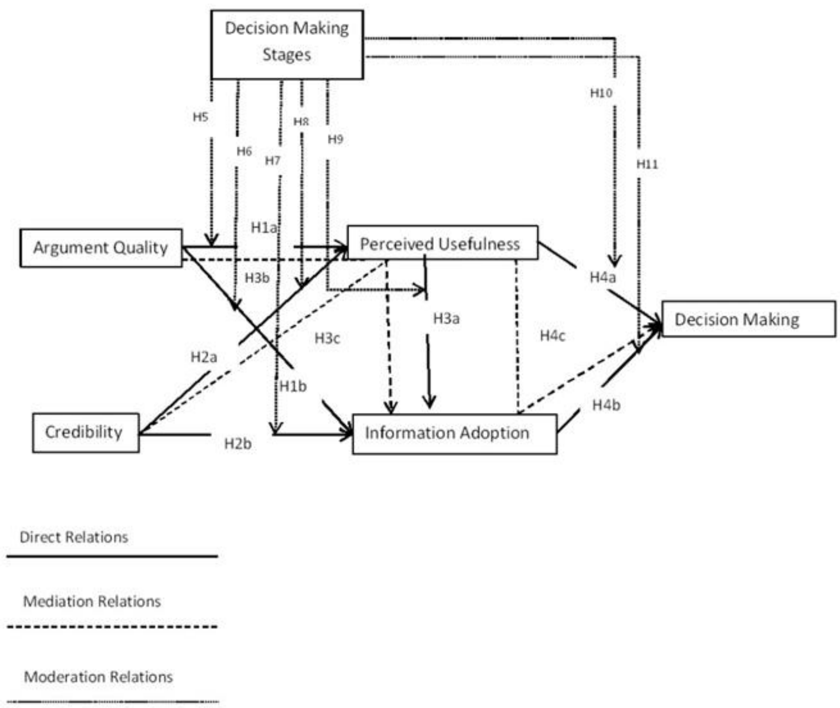

Figure 1. *Hypothesized Model of Decision-Making in OTC*

The conceptual model of information adoption and decision-making in OTC is shown in Figure 1. There are two exogenous constructs –

argument quality and credibility – and two mediators – PU and information adoption. Finally, one endogenous construct is decision-making. The direct and indirect relations among the constructs are examined on the secondary data collected from two OTCs.

METHODS

Measurement of Constructs

Based on the existing literature, the argument quality of posts in a thread has been defined by five items: accuracy, clarity, sidedness, completeness, and relevancy. All the measurement items have been analyzed in the previous research literature (e.g., Cheung et al., 2009; Cheung, 2014; Chung et al., 2015; Chong et al., 2018; Cheung & Thadani, 2012). In this research, credibility is measured by the trustworthiness of the thread postings and cues presented in posts that point to reliable and validated answers. The credibility of information shared in the OTCs threads is examined by three reflective items that investigate the posts' credibility, consistency of replies, and justification offered in support of the answer by community members. For measuring discourse usefulness, adoption, and decision making, items are adopted from the previous literature (Cheung, 2014; Chung et al., 2015; Chong et al., 2018; Wang & Li, 2019). The helpfulness of replies, applicability, and appropriateness of the queries are analyzed to measure the perceived usefulness of UGC in OTCs. Information adoption is evaluated with two items measuring the intention to use the information and the adoption of solutions offered by fellow members in OTC. Decision-making was a single-item scale that described the extent to which the OP had mentioned the final travel decision based on the replies received in the OTC. The information adoption and decision-making constructs are evaluated from the recipient's response to the previous replies. The queries posted by OPs have been categorized as "Information Search Queries" and "Alternatives Evaluation Queries," the two stages of travel decision-making that have been used as the moderators in the proposed research model.

Sample and Data Collection

With the purpose of investigating the influence of user-generated content's credibility and argument quality on the perceived usefulness, info adoption, and travel decision-making in online travel communities, data was collected from two major OTCs. A total of 852 travel threads consisting of 5,958 travel postings written by OTC members in 2019 and 2020 about tourism in India were extracted and evaluated. The threads that included discourse about Indian tourism, starting with questions and containing at least two answers and OP's comments, were major selection criteria. The "India section" of the OTCs threads was examined for data collection. Further, Thorn Tree threads were selected randomly, but because of the high number of data, every first thread on each page from TripAdvisor was checked, and all those threads were extracted which fit the criteria.

About the OTCs

TripAdvisor is one of the largest travel review platforms that provide tourists' reviews on tourism destinations and service providers worldwide. The TripAdvisor forum is a platform where users from different parts of the world communicate with each other about their travel-specific problems. The travel threads are classified according to the different regions and countries of the world, and it also offers sections on tourism products, services, and discourse themes.

Thorn Tree is an online forum of Lonely Planet, which is a popular travel guidebook that offers worldwide travel information. Lonely Planet developed Thorn Tree to compete in the market and explore social-media opportunities (Butler & Paris, 2016). The online travel community provides thread discussion over the continents, and it offers the discourse platform region-wise. In 2019, Thorn Tree had thirteen million unique global users.

Data Analysis

The available secondary data were analyzed on a five-point Likert scale (ranging from "Very Low" to "Very High") by three authors based on a questionnaire (Appendix A) prepared with items from the literature (Cheung, 2014; Chung et al., 2015; Chong et al., 2018; Wang & Li, 2019). OTCs provide online discourse, which forms a thread of questions and replies written by OTC members in text form. The textual content has been transformed into data for statistical analysis by rating the thread posts on a scale of 1 to 5. The items for argument quality were measured as formative indicators (accuracy, clarity, relevancy, comprehensiveness, and sidedness), while for information credibility, perceived usefulness, and adoption, reflective indicators were used for the path model. Decision-making was a single-item scale. However, in the above studies, the argument quality has been examined as reflective scales with multi-items. But, in this study, the argument quality has been analyzed as a formative construct. The reason for choosing the formative scale is that in previous studies, the users' perceptions were analyzed with survey methods, but in the current research, the coders analyzed the UGC posted on OTCs. Each thread was read three to four times for more clarity of content and context of discourse, and the authors found that a thread could be rated only once for a particular quality dimension. For instance, a thread was read in the context of "information comprehensiveness," and if the members had not provided any information about what the enquirer asked, the comprehensiveness was rated as "very low (1)." If a few aspects of the query were handled, the "low (2)" rating was given. In case half of the query was answered the thread was rated as "moderate (3)," if sufficient information was shared by members to meet the enquirer's needs, comprehensiveness was rated "high (4)," and if the thread provided detailed, complete, wide-ranging information, the thread was coded as "very high (5)." Thus, all the threads were evaluated based on a single-item scale.

Additionally, the nature of single items for argument quality was not reflective. Accuracy, sidedness, clarity, comprehensiveness, and relevancy could not be used interchangeably. Hair et al. (2017a, p. 43) specified that "each indicator for a formative construct captures a specific aspect of the construct's domain." Cohen's Kappa was used to check the inter-coder reliability of two DM stages (McHugh, 2012). The values of Cohen kappa showed nearly strong inter-coder reliability for the DM stage (κ = .859). Intraclass Coefficient Correlation (ICC) was calculated for the reliability test of latent constructs coded by three raters using MODEL 3 with two-way mixed methods for "absolute agreement." The ICC revealed an excellent coefficient correlation (ICC.942) among three raters (Koo & Li, 2016).

The data were analyzed with Smart PLS 3. Usakli and Kucukergin (2018) have proposed some practical guidelines for selecting and using PLS-SEM for research in the review study. PLS-SEM is preferred over CB-SEM (covariance-based SEM) because of the objectives and constructs of the study. Further, PLS-SEM is used if 1) the objective of the research is to predict rather than to confirm (Hair et al., 2018); 2) the proposed theory is not well-established (Wold, 1985; Henseler et al., 2014); 3) while using secondary data in study (Richter et al., 2016); and 4) analyzing formative constructs with ease, devoid of any model adjustments (Diamantopoulos & Riefler, 2011; Hair et al., 2017; Bollen & Davis, 2009).

First of all, this is an exploratory study; as per the authors' knowledge, no previous study has evaluated UGC in OTCs in the context of actual users and explored their behavior. Existing theory on this topic has emerged from the user's perceptions about the UGC posted in OTCs, while this study aims to predict the antecedents and consequences of information usefulness and evaluate the impact on UGC creators' actual decisions. Second, the decision-making stages have been analyzed in this study as a moderator, and the proposed theory has not been used to analyze online discourse in OTCs. Third, this study is entirely based on secondary data in online threads written by OTC users about travel and tourism in India. Lastly, the argument quality has been examined as a formative single-item scale, which is comparatively easy to validate using PLS-SEM.

The measurement and structural model results have been explained in the following sections, followed by the results of hypothesis tests. Also, the MICOM process was used before applying PLS-Multi-Group Analysis (MGA) for calculating the moderator effect of information search and alternatives evaluation in the process of decision-making,

This research does not constitute Human Subjects Research as only publicly available threads were analyzed, and no interaction was carried out with any OTC members. Also, identifiable evidence, such as users' names and images, was eliminated from the collected data, following the ethical practices for using social media records (Moreno et al., 2013).

DATA ANALYSIS AND STUDY FINDINGS

Demographic Information

Data from TripAdvisor.com and Thorn Tree was collected for this study. Table 1 shows the profile of the potential tourists planning their travel in India who had initiated a thread discussion in the OTCs. 34.6% of the tourists were male, and 27.8 % were female. The percentage of foreigners was higher than that of Indians. The table reveals that most queries (64.4 %) were raised for information search, while 36.6 % of queries were related to the alternatives' evaluation for future travels in India. Table 1 also discloses information regarding their places of origin and preferred destinations.

Results of the Measurement Model

The convergent validity, collinearity, and the statistical significance of weights of formatively measured constructs are evaluated for the formative constructs in PLS-SEM. Figure 1 displays the structural model of this study. Table 2 highlights the outer weights with the significance level and VIF values for the latent variables. The comprehensiveness item (0.434, p = 0.001) had the highest weight, whereas accuracy (0.174, p = 0.001) had the lowest weight of all the indicators. All the indicators are statically significant with p <0.05 with the VIF below 3, representing no collinearity issue among the examined indicators (Hair et al., 2019). Also, the redundancy analysis of argument quality was checked using a single global item defined on the literature bases, which worked as an alternative to the argument construct and reflected the same meaning. The convergent validity was found to be 0.78 (p <0.001), which is higher than 0.70 and also acceptable (Hair et al., 2017).

Table 1. *Demographic Summary of Potential tourists (OP in OTCs)*

Indicators	Categories	Sample (n=852) Total Frequency (f)	Percentage (%)
Gender	Male	295	34.6
	Not Disclosed	320	37.6
	Female	237	27.8
DM Stage	Information Search	540	63.4
	Alternate Evaluate	312	36.6
OP' s Need	Accessibility	179	21
	Tour Plan	127	14.9
	Documentation & rules	139	16.3
	Itinerary	117	13.7
	Destination& attractions	117	13.7
	Other	104	12.2
	Accommodation & food	69	8.1
Destination region	North India	285	33.5
	North-East India	76	8.9
	West India	122	14.3
	India	113	13.3
	South India	180	21.1
	Central India	51	6
	East India	25	2.9
Place of Origin	India	305	35.8
	Foreign	366	43
	Not Disclosed	181	21.2

The "convergent validity" was evaluated with the outer loadings of the reflective constructs, which were higher than 0.70 except for the one item of PU (PU2 = .510) and statistically significant with a p-value less than 0.001, and by the "Average Variance Extracted" (AVE), which were above .50 for information adoption, information credibility, and PU. (Hair et al., 2019). Further, the VIF was below three, showing no multicollinearity issue. The reflective assessment in Table 3 also discloses that the rho_A of all the constructs was 0.796, 0.772, and 0.852 for information adoption, credibility, and PU, respectively, above the threshold value (0.70), representing accepted "internal consistency reliability" (Hair et al., 2019).

Table 2. *Assessment of Formative Construct*

Constructs	Indicators	Outer Weights	t Statistics	Outer Loadings	VIF
Argument Quality	Accuracy	0.174	3.941**	0.739	1.876
	Clarity	0.299	7.736**	0.793	1.689
	Sidedness	0.084	2.159*	0.666	1.727
	Comprehensiveness	0.434	9.474**	0.908	2.448
	Relevancy	0.221	5.121**	0.837	2.304

**p<0.001, *p<0.05

Table 3. *Reflective Constructs*

Constructs	Indicators	Outer Loadings	t	VIF	Cronbach's Alpha	rho_A	CR	AVE
Info Adoption	ADOPT1	0.917	163.909*	1.759	0.793	0.796	0.906	0.828
	ADOPT2	0.903	121.739*	1.759				
Credibility	CRED1	0.845	66.075*	1.717	0.772	0.772	0.868	0.686
	CRED2	0.818	61.5*	1.477				
	CRED3	0.822	58.11*	1.615				
Perceived Usefulness	PU1	0.918	166.82*	2.024	0.714	0.852	0.834	0.639
	PU2	0.51	12.83*	1.146				
	PU3	0.901	115.90*	2.066				

*p<0.001

Table 4. *Discriminant Validity Using HTMT*

	Credibility	Decision Making	Info-Adoption	Perceived Usefulness
Credibility				
Decision-Making	0.696			
Info-Adoption	0.614	0.885		
Perceived Usefulness	0.881	0.73	0.675	

The HTMT ratio was calculated to measure the discriminant validity (Hair et al., 2018). The HTMT values for reflective constructs were under 0.85 for different constructs and .90 for similar constructs as disclosed in Table 4 (Henseler et al., 2015; Hair et al., 2019). The HTMT inference criterion was below 1.

Assessment of Structural Model

After validating the measurement model, the R2, Q^2, and model fitness were checked in the structural model.

Table 5. *Values of R^2 and Q^2*

Outcome variables	"R^2"	"R^2 Adjusted"	Q^2
Decision Making	.702	.702	.697
Info-Adoption	.33	.327	.269
Perceived Usefulness	.647	.646	.396

Table 5 demonstrates that the hypothesized model explains 70.2 percent of the variation (R2) of the decision-making of OTC members, 64.7 percent of perceived usefulness, and 33 percent of information adoption. Further, to assess the predictive relevance of the research model, a cross-validated redundancy analysis was examined by following the blindfolding procedure (Stone, 1974; Geisser, 1974). The Q2 for DM, PU, and information adoption are 0.69, 0.39, and 0.26, respectively, which are higher than zero, showing the predictive relevance (Table 5).

Further, the standardized root mean square residual (SRMR) was calculated from PLS-SEM, which specifies a good fit of the model as it is less than 0.08 (0.064), which is the limit of good fit (Hair et al., 2018). Further, the normed fit index (NFI) values of 0.84 are near to the acceptable value (i.e., 9) for good model fit (Byrne, 2010).

Results of Hypothesis Testing

This section summarizes the results of the direct mediation and moderation hypothesis proposed in the model. For the moderating effect of the DM stage, a multi-group analysis was conducted. The results are as follows:

Direct relations among constructs:

All hypotheses were supported, as disclosed in the path coefficient results (Table 6). We found that the influence of argument quality (β = .629, p <.001, H1a supported) and credibility (β = .210, p <.001, H2a supported) were found to be significantly associated with PU. Also, the three antecedents affect information adoption significantly: argument quality (β = .223, p <.001, H1b supported), credibility (β = .094, p <.05, H2b supported), and PU (β = .303, p <.001, H3a supported) with 95% bias-corrected confidence intervals. The PU of OTC threads and information adoption were influencing OPs' travel decision-making significantly (β = .337, p <.001, H4a supported; and (β = .606, p <.001, H4b supported, respectively). The effect size of argument quality and perceived usefulness for information adoption are 0.02 and 0.04, respectively, showing relatively small effect sizes, and the f^2 of credibility is .005 (Table 6), which indicates a weak effect. In contrast, the effect size of argument quality for PU and information adoption for DM were large (Cohn, 1988).

Table 6. *PLS-SEM Results and Hypothesis Testing*

	Hypothesized Paths	Path Coefficient	t Value	95% CI	f^2	Decision
H1a	Argument Quality -> Perceived Usefulness	0.629	17.068**	0.556, 0.7	0.431	Supported
H1b	Argument Quality -> Info-Adoption	0.223	3.902**	0.11, 0.3374	0.02	Supported
H2a	Credibility -> Perceived Usefulness	0.21	5.642**	0.138, 0.283	0.048	Supported
H2b	Credibility -> Info-Adoption	0.094	2.042*	0.001, 0.181	0.005	Supported
H3a	Perceived Usefulness -> Info-Adoption	0.303	6.495**	0.209, 0.393	0.048	Supported
H4a	Perceived Usefulness -> Decision Making	0.337	14.419**	0.291, 0.383	0.267	Supported
H4b	Info-Adoption -> Decision Making	0.606	27.257**	0.562, 0.647	0.867	Supported

**p< .001, *p <.05

Indirect relations among constructs:

For mediation analysis, the bootstrap approach provided by Zhao et al. (2010) was applied. Table 7 discloses the indirect effects of the constructs for travel information adoption and decision-making in OTCs. The table shows that PU has mediated the effect of argument quality (β = 0.191, p <0.001, H3b supported) and credibility (β = 0.064, p <0.001, H3c supported) on information adoption. Further, the influence of PU (β = 0.183, p <0.001, H4c supported) on travel decision-making was mediated by information adoption in OTCs. Further, all the direct and indirect relations were significant and positive; thus, the mediation type was complementary partial mediation for the examined relations.

Table 7. *Results of Mediation Effects Hypothesis Testing*

	Mediation relation	Indirect effect (β)	t	95% CI	Direct Effects	β	Mediation Type	Decision
H3b	Argument Quality -> PU -> Info-Adoption	0.191	5.814**	0.127, 0.257	Argument Quality -> Info-Adoption	0.223**	Partial Mediation	Supported
H3c	Credibility -> PU -> Info-Adoption	0.064	4.445**	0.037, 0.094	Credibility -> Info-Adoption	0.094*	Partial Mediation	Supported
H4c	PU -> Info-Adoption-> Decision Making	0.183	6.545**	0.127, 0.238	Perceived Usefulness -> Decision Making	0.337**	Partial Mediation	Supported

**p<0.001, *p<0.05

Assessment of MICOM and MGA results

In order to evaluate the moderating influence of the decision-making stage, the "measurement invariance" for the information search and alternatives evaluation groups should be acceptable (Henseler et al., 2016). Hence, the measurement invariance for the two groups was evaluated using the MICOM procedure before conducting the PLS-MGA, as recommended by Henseler et al. (2016). A three-step MICOM procedure was run with the permutation of 5,000 samples. As for the two group-specific models, the same setup was used to establish the configural invariance. In step II of Table 8, none of the values of correlation c are significantly different from one, and it can be concluded that the compositional invariance has been established (Henseler et al., 2016). Further, results show that composites' mean values and variances do not significantly differ across both groups (MICOM step 3a, 3b). Thus the 3rd step of MICOM concludes that the variance measurement was also established (Henseler et al., 2016), and the PLS-MGA was applied (Table 9).

Based on the PLS-MGA and permutation results, significant differences were reported across the two groups (Table 9) in the effects of argument quality ($\Delta\ \beta = .250$, $p = .039$) and PU ($\Delta\ \beta = -.220$, $p = .030$) on information adoption and the effects of PU on DM ($\Delta\ \beta = -.100$, $p = .047$). Argument quality does not significantly influence information adoption for queries that sought alternatives evaluation. Specifically, the findings stated that the effect of information adoption on DM was higher for information search. The effect of argument quality on PU and PU's effect on information adoption and DM were lower for information search than for alternatives evaluation, but the difference was not statistically significant. One of the interesting findings is that the credibility influences the adoption of information insignificantly for both groups individually, but this effect is statistically significant in overall data.

Table 8. *Results of MICOM for DM Stage*

MICOM STEP 2					MICOM STEP 3a				MICOM STEP 3b			
Constructs	**Correlation c**	**5% quantile of the empirical distribution of C cu**	**p**	**Compositional invariance established?**	**Differences of composite's mean value (=0)**	**95%b CI**	**p**	**Equal mean values?**	**Logrithm of the composite's Variance (=0)**	**95%b CI**	**p**	**Equal variance?**
Argument Quality	0.99	0.981	0.307	YES	-0.059	0.136,0.142	0.412	Yes	-0.158	0.199, 0.206	0.13	Yes
Credibility	0.999	0.999	0.168	YES	-0.08	0.14, 0.139	0.261	Yes	-0.136	0.175, 0.177	0.133	Yes
DM	1	1	0.206	YES	-0.053	0.135, 0.145	0.447	Yes	-0.034	0.109, 0.119	0.555	Yes
Info-Adoption	1	1	0.428	YES	-0.048	0.141, 0.138	0.504	Yes	0.088	0.142, 0.147	0.227	Yes
PU	0.997	0.997	0.058	YES	0.021	0.143, 0.146	0.765	Yes	-0.167	0.203, 0.213	0.115	Yes

Table 9. *Results for PLS-MGA for DM stages*

		Path Coefficients		t-value and Significance level			P-value differences (one-tailed)		
Hypothesis	**Relationship**	**Information Search**	**Alternatives Evaluation**	**Information Search**	**Alternatives Evaluation**	**Path Coefficient Differences**	**Permutation p-Values**	**Henseler's MGA**	**Supported**
H5	Argument Quality ->PU	0.605	0.649	11.953***	12.355***	-0.044	0.572	0.547	**No**
H6	Argument Quality -> Info-Adoption	0.319	0.069	4.659***	0.680	0.25	0.029	0.039	**Yes**
H7	Credibility -> Info-Adoption	0.084	0.081	1.438	1.085	0.003	0.978	0.966	**No**
H8	Credibility -> PU	0.225	0.215	4.387***	3.963***	0.01	0.905	0.898	**No**
H9	PU -> Info-Adoption	0.231	0.451	4.059***	5.457***	-0.22	0.021	0.030	**Yes**
H10	PU -> Decision Making	0.299	0.399	10.031***	9.909***	-0.1	0.039	0.047	**Yes**
H11	Info-Adoption -> Decision Making	0.632	0.558	23.377***	13.98***	0.074	0.110	0.123	**No**

DISCUSSION

Online travel communities offer vast information for the users and provide a platform for the members to communicate with each other and get assistance for their travel planning. The OTCs work as a social media tool where information is generated by writing posts, replies, and questions on travel-related topics, and these enable information sharing on a large scale. This study has evaluated the consequences of the argument quality and credibility on the perceived usefulness of OTC content and information adoption in the OTCs. Lastly, OTC members' travel decision-making was also analyzed. The results show that argument quality has significantly influenced the PU and information adoption in OTC. The results support the previous findings (Chong et al., 2018). The comprehensiveness of the information offered by the repliers to the OP is the significant indicator for strengthening the argument quality of a thread, followed by the clarity and relevancy of information. The OTC members must carry on the discussion in a thread on the same topic started by the OP in the initial post, and the complete information given by the members becomes helpful in knowledge adoption and decision-making.

Further, the credibility of OTC content is an essential determinant for influencing the perceived usefulness of the OTC members, as also stated by Chung et al. (2015) and Chong et al. (2018). Travel postings containing consistent, reliable information supported by references, external links, and justification are perceived as more credible. The high outer loading values indicate that the credibility was high in the OTCs and it directly influences perceived usefulness and information. It was hypothesized that the perceived usefulness of information would influence information adoption and travel decision-making. The study findings have supported the proposed hypothesis, consistent with Cheung's (2014) and Wang and Li's (2019) results. The helpfulness, feasibility, and applicability of OTC information are influential in the adoption of the information by the OP and their intention to use the information for further travel decision making. Also, PU acts as a mediator for the influence of credibility and argument quality on UGC adoption and partially mediates the relationship between information adoption and travel decision-making positively. Thus, it becomes crucial for the OTCs to formulate guidelines for the community members to post useful information that can be applied in the specified condition. Also, the community members should be motivated to write clear, complete, and relevant information to be adopted by the OP to solve travel queries.

This study has also investigated the moderator effect of information search and evaluation on the specified path model. The decision-making of a tourist starts with "need recognition," followed by "information search and evaluation." The data in this research was categorized according to the two stages of travel decision-making. Results found that the path coefficients were significantly lower for the information search cluster than the alternatives evaluation for the influence of PU on travel decision-making and information adoption and path coefficients were significantly higher for information search for the influence of argument quality on information adoption in both OTCs. Kim et al. (2007) also found that information-seeking questions seek clarity and accuracy in responses and discussion-seeking questions pursue consensus in replies, and for opinion-type questions, questioners' rate highly for socio-emotional support.

This study has used data from two significant OTCs that offer travel solutions to Indians and foreigners for their travel in India, and in which Indians and foreigners also participate in the community to discuss issues regarding travel planning in India. The findings propose some practical guidelines for both OTCs.

Theoretical and Practical Implications

This research study is one of the initial attempts to analyze the online discourse in OTCs about travel in India. The study has investigated the factors influencing online discourse's perceived usefulness and consequences. The study offers imperative theoretical inferences that enrich the prior research on UGC in OTCs. The study has found that credibility and argument quality have been significant determinants influencing the perceived usefulness of the discourse and motivating the enquirers to adopt online information. Further, the study also implies that the perceived usefulness significantly influences the effect of its antecedents on information adoption, which are major factors determining travel decision-making. Finally, decision-making stages have been examined in this study. It was revealed that the effects of argument quality and PU on information adoption and the effects of PU on DM were significantly different between the two stages, thus significantly contributing to OTCs and travel decision studies. The argument quality was a higher and more significant factor of PU for information search, and the influence of PU on information adoption and decision-making was more significant for the alternatives evaluation stage.

This study is a base for studies aiming to investigate factors influencing the usefulness of UGC and its consequences on travel decision-making. Further, this study can also be used to understand how discourse in OTCs can be investigated and is a pioneer for researchers wanting to evaluate UGC on social networking sites. This study has tested a multifaceted research model that has investigated various types of relations among the constructs to understand how tourists use OTCs for travel planning and decision-making.

This research offers practical implications for online travel communities, travel sites generating eWOM, social media authorities, and the tourism industry. With the increasing number of social networking sites and internet users, our study provides OTC practitioners guidelines for determining the usefulness of OTC information and travel decision-making. The results suggest that the OTC designers should consider the credibility of the UGC while ensuring the accuracy, completeness, and relevance of UGC posted by members. The high-quality information shared by fellow members is considered more valuable and significantly influences their intention to adopt the proposed advice recommendations. The OTC managers should ensure that the members answering the OP should offer them applicable information, which the OP can adopt. The OTC managers need to set guidelines for members for writing a query or replying to any question. The guidelines should focus on high relevance and accuracy of information to be shared by community members. Specific consideration should be given to the reliability of information and the external references; links shared should be functioning and applicable. The increase of useful content generated in an OTC would significantly influence the members to accept the information and support their travel decisions.

Second, the use of social media by tourism service providers has been increasing regularly. They use social networking sites for promotional and marketing purposes and the sites act as the platform for service users to share their experiences and interact online about services consumed. The content shared on the social media platforms influences the PU of the site; thus, the e-service providers should consider the various alternatives of social media while deciding which platform is perceived as more useful and popular among its consumers. The findings reveal that the OTC is the platform used overseas to interact with tourists about any particular destination or city of a country. Thus, the worldwide approach of OTCs enables tourism service providers and destinations to utilize the travel forums to understand the needs and demands of the potential tourists at a destination. The online interactions provide clues about constraints regarding any destination, accommodation, or transport service. The online interactions of the OTC members can provide suggestions to service providers on which areas of services need improvement and which are in demand. Further, the UGC in OTCs offers hints regarding travel trends. Service providers must explore the potential of SM sites to extend their markets and understand consumers' preferences.

CONCLUSIONS

The current article aimed to investigate online discourse posted by tourists on OTCs, in the context of perceived usefulness and decision-making. The study has offered significant findings regarding essential factors of the user-generated content that help the tourists in information adoption and decision-making. The users' perception of argument quality and source quality has been analyzed by prior researchers, while this study has investigated the UGC posted by actual tourists. The usefulness of shared information makes the tourists adopt the information and plan accordingly. The community members are significantly influenced by the information's usefulness and adoption intentions in finalizing their travel decisions. This study added to the existing research about travel decisions and UGC in OTCs. Further, the analysis of the two decision-making stages has added to the knowledge of the travel decision behavior of tourists.

The current study faces several limitations: first, this study has analyzed secondary data available on the online travel communities' sites in travel postings. So as to generalize the research model, future researchers can collect data from survey samples from actual tourists participating in OTCs and undertaking tourism activities. Also, this study has emphasized only those threads written on India; other country posts can also be studied; thus, it is suggested that future research can be replicated using OTC postings done from other cultural backgrounds to investigate whether there will be a difference in tourist’s perceptions.

Second, the study analyzed all UGC on various tourist needs; future studies could augment the inquiry model in precise travel needs, for example, accommodation or transportation or tour planning, to investigate the differences in the determinants and consequences of PU for various tourists' needs. Also, the determinants of information adoption and decision-making were limited in this study. Credibility and argument quality can be examined as multi-dimensional concepts (Chong et al., 2018). Finally, only two stages of decision-making were investigated in this study;

future research can be carried out with other moderators as OTC members' characteristics to enhance the study's usefulness.

REFERENCES

Agag, G. M., & El-Masry, A. A. (2017). Why do consumers trust online travel websites? Drivers and outcomes of consumer trust toward online travel websites. *Journal of Travel Research, 56*(3), 347-369.

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: cognitive absorption and beliefs about information technology usage. *MIS Quarterly, 24*(4), 665-694.

Alsabawy, A. Y., Cater-Steel, A., & Soar, J. (2016). Determinants of perceived usefulness of e-learning systems. *Computers in Human Behavior, 64*, 843-858.

Angst, C. M., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS quarterly*, 339-370.

Ayeh, J. K., Au, N., & Law, R. (2013). Predicting the intention to use consumer-generated media for travel planning. *Tourism Management, 35*, 132-143.

Bhattacherjee, A., & Sanford, C. (2006). Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model. *MIS Quarterly, 30*(4), 805–825.

Bollen, K. A., & Davis, W. R. (2009). Causal indicator models: Identification, estimation, and testing. *Structural Equation Modeling: A Multidisciplinary Journal, 16*(3), 498-522.

Brand, D. J. (2016). Automatic Prediction of Comment Quality (Doctoral dissertation, Stellenbosch: Stellenbosch University).

Butler, G., & Paris, C. M. (2016). Reaching the end of the unbeaten path? An analysis of Lonely Planet's digital media "requiem". *Anatolia, 27*(3), 377–388.

Byrne, B. M. (2010). *Structural Equation Modeling with AMOS*: *Basic concepts, applications and programming* (2nd ed.). New York: Routledge. doi: 10.4324/9781410600219

Capriello, A., Mason, P. R., Davis, B., & Crotts, J. C. (2013). Farm tourism experiences in travel reviews: A cross-comparison of three alternative methods for data analysis. *Journal of Business Research, 66*(6), 778-785.

Chan, Y. & Ngai, E. (2011). Conceptualising electronic word of mouth activity. Marketing Intelligence and Planning, 29(5), 488-516.

Chen, C. D., & C. S. Ku. (2012). Building Member's Relationship Quality Toward Online Community from the Elaboration Likelihood Model Perspective. Proceedings of the Pacific Asia Conference on Information Systems paper 126, Hochiminh City, Vietnam

Chen, J. S. (1998). The tourists' cognitive decision-making model. *The Tourist Review, 53*(1), 4-9.

Cheung, C. M., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision support systems, 54*(1), 461-470.

Cheung, C.M., Lee, M.K., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: the adoption of online opinions in online customer communities. *Internet Research, 18*(3), 229-247.

Cheung, M. Y., Luo, C., Sia, C. L., & Chen, H. (2009). Credibility of electronic word-of-mouth: Informational and normative determinants of online consumer recommendations. *International journal of electronic commerce, 13*(4), 9-38.

Cheung, R. (2014). The influence of electronic word-of-mouth on information adoption in online customer communities. *Global Economic Review, 43*(1), 42-57.
Chong, A. Y. L., Khong, K. W., Ma, T., McCabe, S., & Wang, Y. (2018). Analyzing key influences of tourists' acceptance of online reviews in travel decisions. *Internet Research, 28*(3), 564-586. https://doi.org/10.1108/IntR-05-2017-0212
Choudhary, P., & Gangotia, A. (2017). Do travel decision-making styles and gender of generation Y have any association with travel information share on social networking sites?. *Journal of Hospitality and Tourism Technology, 8*(2), 152-167.
Chung, N., Han, H., & Koo, C. (2015). Adoption of travel information in user-generated content on social media: the moderating effect of social presence. *Behaviour & Information Technology, 34*(9), 902-919.
Cohn, J. (1988). *Statistical power analysis for the behavioral sciences*. Lawrence Earlbam Associates, Hillsdale, NJ.
Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.
Dedeoglu, B.B. (2019). Are information quality and source credibility really important for shared content on social media? The moderating role of gender. *International Journal of Contemporary Hospitality Management, 31*(1), 513-534. https://doi.org/10.1108/IJCHM-10-2017-0691
Diamantopoulos, A., & Riefler, P. (2011). Using formative measures in international marketing models: A cautionary tale using consumer animosity as an example. In *Measurement and Research Methods in International Marketing* (pp. 11-30). Emerald Group Publishing Limited. Bingley.
Fang, J., Chen, L., Wang, X., & George, B. (2018). Not all posts are treated equal: An empirical investigation of post replying behavior in an online travel community. *Information & Management, 55*(7), 890-900.
Filieri, R., & McLeay, F. (2014). E-WOM and accommodation: An analysis of the factors that influence travelers' adoption of information from online reviews. *Journal of travel research, 53*(1), 44-57.
Gal-Tzur, A., Bar-Lev, S., & Shiftan, Y. (2020). Using question & answer forums as a platform for improving transport-related information for tourists. *Journal of Travel Research, 59*(7), 1221-1237.
Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika, 61*(1), 101-107.
George, D., & Mallery, P. (2010). *SPSS for Windows step by step. A simple study guide and reference* (10. ed.). GEN, Boston, MA: Pearson Education, Inc.
Gretzel, U., Yoo, K. H., & Purifoy, M. (2007). Online Travel Review Study: Role & Impact of Online Travel Reviews. Laboratory for Intelligent Systems in Tourism, Texas A&M University. LIST 02-07-01.
Gvili, Y., & Levy, S. (2016). Antecedents of attitudes toward eWOMcommunication: differences across channels. *Internet Research, 26*(5), 1030–1051.
Hair, J. F., Hult, T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least square structural equation modeling (PLS-SEM)*. Sage Publications.
Hair, J.F., Sarstedt, M., Ringle, C.M., & Gudergan, S.P. (2018). *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage, Thousand Oaks, CA.
Hair, J.F., Risher, J.J., Sarstedt, M., & Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hajli, N., Wang, Y., & Tajvidi, M. (2018). Travel envy on social networking sites. *Annals of Tourism Research, 73*, 184–189. https://doi.org/10.1016/j.annals.2018.05.006

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., ... & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational research methods, 17*(2), 182-209.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*(1), 115-135.

Henseler, J., Ringle, C.M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*(3), 405-431.

Hu, Y. H., Chen, K., & Lee, P. J. (2017). The effect of user-controllable filters on the prediction of online hotel reviews. *Information & Management, 54*(6), 728-744.

Kim, J. J., Fesenmaier, D. R., & Johnson, S. L. (2013, July). The effect of feedback within social media in tourism experiences. In *International conference of design, user experience, and usability* (pp. 212-220). Springer, Berlin, Heidelberg.

Kim, S., Oh, J. S., & Oh, S. (2007). Best-answer selection criteria in a social Q&A site from the user-oriented relevance perspective. *Proceedings of the American Society for Information Science and Technology, 44*(1), 1-15.

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of chiropractic medicine, 15*(2), 155-163.

Lee, H., Reid, E., & Kim, W. G. (2014). Understanding knowledge sharing in online travel communities: antecedents and the moderating effects of interaction modes. *Journal of Hospitality & Tourism Research, 38*(2), 222-242.

Li, C. Y. (2013). Persuasive messages on information system acceptance: A theoretical extension of elaboration likelihood model and social influence theory. *Computers in Human Behavior, 29*(1), 264-275.

Li, H. & Liu, Y. (2014). Understanding post-adoption behaviors of e-service users in the context of online travel services. *Information and Management, 51*(8),1043-1052.

Li, L., He, D., & Zhang, C. (2019). Characterizing High-Quality Answers for Different Question Types on Academic Social Q&A Site. In *ISSI* (pp. 2670-2671).

Li, L., Zhang, C., & He, D. (2020). Factors influencing the importance of criteria for judging answer quality on academic social Q&A platforms. *Aslib Journal of Information Management, 72*(6),887-907.

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism management, 29*(3), 458-468.

Matute, J., Polo-Redondo, Y., & Utrillas, A. (2016). The influence of EWOM characteristics on online repurchase intention mediating roles of trust and perceived usefulness. *Online Information Review, 40*(7), 1090-1110.

McHugh, M. L. (2012). Interrater reliability: the kappa statistic. *Biochemiamedica, 22*(3), 276-282.

McKinney, V., Yoon, K., & Zahedi, F. M. (2002). The measurement of web-customer satisfaction: An expectation and disconfirmation approach. *Information systems research, 13*(3), 296-315.

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.

Moreno, M. A., Goniu, N., Moreno, P. S., & Diekema, D. (2013). Ethics of social media research: common concerns and practical considerations. *Cyberpsychology, behavior, and social networking, 16*(9), 708-713.

Munar, A. M., & Jacobsen, J. K. S. (2014). Motivations for sharing tourism experiences through social media. *Tourism management, 43*, 46-54.

Oriade, A., & Robinson, P. (2019). Prosuming tourist information: Asking questions on Trip Advisor. *International Journal of Tourism Research, 21*(1), 134-143.

Owusu, R. A., Mutshinda, C. M., Antai, I., Dadzie, K. Q., & Winston, E. M. (2016). Which UGC features drive web purchase intent? A spike-and-slab Bayesian Variable Selection Approach. *Internet Research, 26*(1), 22–37.

Papathanassis, A., & Knolle, F. (2011). Exploring the adoption and processing of online holiday reviews: A grounded theory approach. *Tourism Management, 32*(2), 215-224.

Park, J. H., Gu, B., Leung, A. C. M., & Konana, P. (2014). An investigation of information sharing and seeking behaviors in online investment communities. *Computers in Human Behavior, 31*, 1-12.

Petty, R.E., & Cacioppo, J.T. (1986). The Elaboration Likelihood Model of Persuasion. *Advances in Experimental Social Psychology, 19*, 123–205.

Richter, N. F., Cepeda-Carrion, G., Roldán Salgueiro, J. L., & Ringle, C. M. (2016). European management research using partial least squares structural equation modeling (PLS-SEM). *European Management Journal, 34*(6), 589-597.

Savolainen, R. (2015). Providing informational support in an online discussion group and a Q & A site: The case of travel planning. *Journal of the Association for Information Science and Technology, 66*(3), 450-461.

Sher, P. J., & Lee, S. H. (2009). Consumer skepticism and online reviews: An elaboration likelihood model perspective. *Social Behavior and Personality: an international journal, 37*(1), 137-143.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the royal statistical society: Series B (Methodological), 36*(2), 111-133.

Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information systems research, 14*(1), 47-65.

Tilly, R., Fischbach, K., & Schoder, D. (2015). Mineable or messy? Assessing the quality of macro-level tourism information derived from social media. *Electronic Markets, 25*(3), 227-241.

Tormala, Z. L., & Petty, R. E. (2004). Source credibility and attitude certainty: A metacognitive analysis of resistance to persuasion. *Journal of Consumer Psychology, 14*(4), 427-442.

Twumasi, A., & Adu-Gyamfi, K. (2013). The impact of social networking sites on the purchasing behaviours of online travel community members. *Information and Knowledge Management, 3*(11), 105-111.

Usakli, A., & Kucukergin, K. G. (2018). Using partial least squares structural equation modeling in hospitality and tourism: do researchers follow practical guidelines?. *International Journal of Contemporary Hospitality Management, 30*(11), 3462-3512.

Wang, P., & Li, H. (2019). Understanding the antecedents and consequences of the perceived usefulness of travel review websites. *International Journal of Contemporary Hospitality Management, 31*(3), 1086-1103. https://doi.org/10.1108/IJCHM-06-2017-0380

Wold, H. (1985). *Encyclopedia of statistical sciences. Partial least squares*. Wiley, New York, 581-591.

Xie, G. X., & Boush, D. M. (2011). How susceptible are consumers to deceptive advertising claims? A retrospective look at the experimental research literature. *The Marketing Review, 11*(3), 293-314.

Yang, C. C., & Brown, B. B. (2015). Factors involved in associations between Facebook use and college adjustment: Social competence, perceived usefulness, and use patterns. *Computers in Human Behavior, 46*, 245-253.

Yang, J., Mai, E., & Ben-Ur, J. (2012). Did you tell me the truth?: The influence of online community on eWOM. *International Journal of Market Research, 54*(3), 369-389.

Zhao, X., Lynch Jr, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of consumer research, 37*(2), 197-206.

Zhou, T. (2017). Understanding location-based services users' privacy concern. *Internet Research, 27*(3), 506–519.

APPENDIX A. *Questionnaire relating to the research model*

Dimensions	**Measurement Items**	**References**
Argument Quality		
Accuracy	The repliers in OTC threads provided accurate and correct information.	(Cheung, 2014; Chung et al., 2015; Chong et al., 2018; Wang & Li, 2019; Fu & Oh, 2019)
Clarity	The repliers in OTC threads provided clear and unblemished information.	
Sidedness	The OTC members provide unbiased information to the initial poster, and both pros and cons are discussed in the thread.	
Comprehensiveness	The replies in a thread provide sufficient information for the task with adequate breadth and depth.	
Relevancy	The user-generated content in OTC threads is relevant to the initial query and the original poster's needs.	
Credibility		
CRED 1	The user-generated content in OTC threads is credible.	(Chung et al., 2015; Chong et al., 2018)
CRED 2	The user-generated content in OTC threads is consistent in the entire thread.	
CRED 3	The repliers in OTC threads justified their answers.	
Perceived Usefulness		
PU 1	The user-generated content in OTC was helpful for the initial poster.	(Davis, 1989; Cheung 2014; Chong et al., 2018)
PU 2	The user-generated content in OTC was appropriate for the initial poster.	
PU 3	The user-generated content in OTC was applicable for the initial poster.	
Information Adoption		
ADOPT 1	The initial poster intends to adopt the information shared in the OTC.	(Chung et al., 2015; Chong et al., 2018)
ADOPT 2	The initial poster intends to follow the information shared in the OTC for further decision.	
Decision-Making		
DM	After reading and participating in online discourse in OTC, the initial poster has made the final decision in the thread.	(Cheung 2014; Chong et al., 2018; Wang & Li, 2019)
Argument Quality (single-global item)		
	The replies in the thread have provided enough strength to their arguments while replying to a query. The overall argument quality of replies is good.	(Chong et al., 2018; Wang & Li, 2019)

NOTE: "The items of the Argument Quality dimension were rated on a five-point Likert scale ranging from *very low* to *very high*, and the items of the reflective constructs, e.g., UGC Credibility, Information Adoption, Perceived Usefulness, and Decision-making, have been rated on Five-point Likert scale ranging from *very* low to very high."

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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON HOSPITALITY EMPLOYEES' WORK OUTCOMES

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ABSTRACT

The aim of this systematic literature review is to analyze the existing literature on the impact of artificial intelligence (AI) on employee work outcomes in the hospitality industry context. This paper systematically reviews the association between AI and employee work outcomes through an extensive literature review of published peer-reviewed English articles. Eighteen articles have been found in 12 journals and analyzed through deductive approach. The findings were synthesized into three major themes: enablers or inhibitors of AI adoption, the type of AI-related technique, outcomes of AI adoption. Well-being, turnover intention, and job engagement were identified as the most significant and most commonly studied outcomes of AI adoption.

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INTRODUCTION

The emergence of the latest technology and machines with analytical intelligence has contributed significantly to the fourth industrial revolution (Behl et al., 2021). Industry 4.0 is often characterized by the emergence of AI and robots (Hirschi, 2018). AI technology is among the world's most innovative inventions (Samala et al., 2020), and is increasingly becoming a part of workplaces around the world today (Khaliq et al., 2022). As a matter of fact, the development of digital technologies such as AI, internet of things (IoT) and big data plays an important role in the success of businesses and

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provides them with innovation and sustainable development (Vial, 2019). The hospitality industry has also started using cutting-edge systems based on AI and robot-based applications and services (Nam et al., 2021) because innovation plays a crucial role in the success of the hospitality industry (Úbeda-García et al., 2018).

AI and automated robots have caused many changes in the hospitality organizations (Yang & Chew, 2021). Artificial intelligence and robotics have remarkable effects on job profiles, employee relations in the workplace, working hours and wage patterns (Li et al., 2019). Thus, AI is modifying the manner people work, and influencing jobs and tasks (Braganza et al., 2021). With the emergence of AI, the hospitality sector has been faced with the fear of losing the human element (Saini & Bhalla, 2022), because employees and the human touch are part of the hospitality product (Bowen & Morosan, 2018). Hence, it is essential to seek answers to the query of how AI technologies will affect hospitality employees, as it will provide the opportunity for managers to identify the opportunities and threats that may arise from technology and to guide them in developing competencies suitable for the emerging technology. Although prior research has recently worked on AI outcomes, most of these were predominantly based on the customers' perspective (Prentice et al., 2020; Li et al., 2022). Therefore, drawing on the organizational change theory, this paper seeks to provide a systematic review of existing AI-related studies to synthesize the impacts of AI on the employee work outcomes in the hospitality context.

The contribution of this paper is twofold. First, to the authors' knowledge, the existing paper is a first attempt to investigate systematically the association between AI and employee work outcomes in the hospitality context. This paper contributes to the existing literature by providing a new perspective to understand the factors that enable or inhibit the adoption of AI, the type of AI-related technique, and the impact of AI on employee work outcomes from the organizational change theory perspective. Second, the work outcomes resulting from the adoption of AI in organizations are expected to guide future research. At the same time, the factors that enable or inhibit the adoption of AI presented in the theoretical model can help hospitality managers take the necessary measures to promote the adoption and development of technological innovations. In keeping with the purpose of the research, the following research questions guide our review:

RQ1. What are the factors that enable or inhibit the adoption of AI in the hospitality industry?

RQ2. What type of AI-related technique is used in organizations?

RQ3. What is the impact of AI on the work outcomes of hospitality employees?

LITERATURE REVIEW

AI and Work Outcomes

The term AI was first used by John McCarthy. The use of AI in the business dates back to the 1980s, and emerging technologies have led organizations to implement technologies such as robots, smart systems, and software and hardware (Borges et al., 2021). AI concept has received a lot of attention for its impact on the economy and its power to transform industries (Huang et al., 2022). AI is a category of intelligent technologies that includes sub-fields such as knowledge representation, reasoning, planning, decision making, optimization, machine learning, and meta-heuristic algorithms (Latah & Toker, 2018). There are different approaches to defining AI. As seen in Table 1, different definitions of AI focus on human-like abilities of AI such as thinking, interpreting, and learning. Therefore, AI is expressed as a system that thinks and acts like a human (Tussyadiah, 2020). On the other hand, AI, which enables machines to think and act like humans, has abilities such as intelligence, learning, and reasoning (Kar et al., 2022). Accordingly, intelligence in AI refers to the ability to learning, thinking, solving problems, reasoning, and integrate functions such as planning, perception, and attention. Second, reasoning in AI is based on logic and enables machines to think rationally and apply deductive and inductive approaches. Finally, learning in AI is the ability of an AI program to learn from its data. Moreover, AI provides mechanisms for machines to accumulate and learn information, helping machines obtain information from various sources, process information, and then apply that knowledge (Alansari et al., 2021). Hence, AI not only seeks to follow previously defined processes to simulate human behavior, but also seeks to imitate human learning (Borges et al., 2021).

It is known that the use of intelligent machines will cause changes in the functioning of organizations and the conduct of activities (Pereira et al., 2023). In other words, technological innovations such as AI and robots are expected to have a significant impact on changing organizational processes and improving organizational capabilities (Budhwar et al., 2022). AI, which requires employees to develop skills in accordance with the emerging technology, provides positive work outcomes by enabling them to work more systematically in organizations (Ruel & Njoku, 2021). Studies have shown that AI and related technologies have positive outcomes, such as increasing employee job performance (Prentice et al., 2020), productivity (Wirtz et al., 2019), and job satisfaction (Castellacci & Viñas-Bardolet, 2019). According to Nam et al (2021), employees are adopting AI technology because it increases employee productivity, and as a result, hotels place an emphasis on implementing AI. In this sense, organizations aiming to achieve positive work outcomes are more motivated to adopt AI (Yu et al., 2023). Therefore, it is necessary to focus on the interaction and cooperation between AI and human employees through continuous learning in organizations (Wilkens, 2020).

In addition to the positive work outcomes of the adoption of AI in organizations, some negative outcomes are also mentioned. Although most jobs are difficult to automate in industries with high human interaction, such as the hospitality industry (Li et al., 2019), employees may think that their jobs are in danger due to AI applications, which may lead them to leave the organization (Yu et al., 2023). Similarly, negative attitudes and behaviors of employees towards emerging technologies such as AI may cause some negative employee outcomes such as high employee turnover rate, job insecurity, and stress (Brougham & Haar, 2018; Budhwar et al., 2022). Moreover, Wright and Schultz (2018) state that AI and automation may reduce the quality of human interactions, cause a feeling of isolation and disconnection, and ultimately affect the well-being of individuals. Hence, in order to reap the benefits and positive consequences of AI, it is important for authorities or managers to understand and analyze the threats and opportunities that such technologies may pose (Yu et al., 2023).

Table 1. *Definition of key terms*

Key terms/References	Definitions
Artificial intelligence McCarthy (2007)	"Artificial intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs."
Mikalef and Gupta (2021)	"AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals."
Lee et al. (2019)	"Artificial intelligence is the intelligent systems created to use data, analysis and observations to perform certain tasks without needing to be programmed to do so."
Kopka and Grashof (2022)	"One of the newer trends of this digitalization process is the so called artificial intelligence (AI), which is often seen as a panacea for all kinds of problems."
Raisch and Krakowski (2021)	AI refers to "machines performing cognitive functions usually associated with human minds, such as learning, interacting, and problem solving."
Attitudinal outcomes Fung (2014)	"Attitudinal outcomes are team outcome factors that cover employee satisfaction, commitment and trust in management."
Cohen and Bailey (1997)	"Attitudinal outcomes refer to the affective responses people have towards their work environment, such as organizational commitment and job satisfaction."
Behavioral outcomes Fu and Cheng (2014)	"Behavioral outcomes refer to employees' reactions regarding perceptions of unfulfilled expectations and promises."

Organizational Change Theory

Organizational change theory is based on Lewin's Planned Change Model (Armenakis & Bedeian, 1999). Lewin (1951) theorizes successful organizational change under three phases: unfreezing, change (moving), and refreezing. Lewin (1951) emphasizes that unfreezing is necessary in order to avoid resistance in the process of change (Hassan, 2018). In the unfreezing phase, the current attitudes and perceptions of the organization or individuals need to be unfrozen in order to achieve successful organizational change (Friday & Friday, 2003). In other words, this phase is about the organization or individuals having sufficient motivation to make the change. The moving phase involves individuals developing a new perspective through training, and open communication and encouragement to participate in change are important during this phase (Lee, 2006). The refreezing phase focuses on the sustainability of change and aims to ensure that organizations do not revert to their previous state (Page & Schoder, 2018). Since this phase requires reinforcing the new behaviors and attitudes of individuals, continuous training and procedures and policies within the system should be at the forefront at this phase (Friday & Friday, 2003). Organizational change theory is based on the examination of the factors necessary for organizations to achieve successful organizational change (Al-Haddad & Kotnour, 2015). Hence, this theory was chosen because it focuses on the mechanisms needed to motivate and ultimately implement change in organizations.

METHODOLOGY

This section describes the approach used in the study. A Systematic Literature Review (SLR) was conducted to review and analyze study findings on the effect of AI on employee outcomes in hospitality sector. The method used in the paper follows the protocol defined by Kitchenham (2004). This section consists of four steps: (i) search methods, (ii) inclusion and exclusion criteria, (iii) study relevance and quality assessment, and (iv) analysis and synthesis.

The databases included Web of Science (WoS), Google Scholar, and EBSCO Hospitality and Tourism Complete. Three sets of keywords were searched in databases, using the “advanced search” feature: (i) keywords relating to the AI and associated technologies, (ii) keywords relating to the employee job outcomes, and (iii) keywords relating to the hospitality and tourism field. Consequently, the search terms were a combination of ("Robo*" OR "AI" OR "artificial intelligence" OR "intelligent automation" OR "intelligent agent" OR "human-agent interaction" OR "computer science" OR "robot-human interaction" OR "semantic web" OR "neural networks" OR "machine learning" OR "industry 4.0" OR "intelligent systems" OR "service automation") AND ("employee outcomes" OR "employee" OR "personnel" OR "workplace" OR "work environment" OR "job" OR "organization" OR "labor") AND ("Tourism" OR "travel" OR "hotel" OR "hotels" OR "visit" OR "hospitality" OR "aviation" OR "tourist" OR "leisure" OR "hospitality management" OR "restaurant"). The initial search yielded a total of 7,618 studies.

In the second step, a set of inclusion and exclusion criteria were utilized to define the limits of the SLR. We limited our research to peer-reviewed articles written in the English language. Our study was based on articles published in leading journals because quality journals greatly aid academic growth (Judge et al., 2007). Studies were included if they were conducted on hotel or restaurant employees in the hospitality context, investigated AI in a hospitality context, examined the impact of AI and related technologies on employee outcomes. We also included articles using both review, conceptual and empirical methods. We did not specify any time limit on data collection for an in-depth and comprehensive view of the topic. After inclusion and exclusion criteria were applied, 249 articles remained for the detailed analysis.

The third step involved assessing the relevance and quality of the studies. Our initial goal was to identify all studies related to AI in the context of hospitality. During this process, the title and abstract were read for each of the 249 identified studies, and 223 were retained after removing duplicates. At the end of this round of the review, 26 studies remained. We included articles that explored AI as the main topic, used a data sample from the hospitality industry, and linked AI to at least one employee outcome. The relevance and quality of these articles were evaluated by reading the entire article. Two co-authors reviewed each study independently and then evaluated their quality against various criteria. Studies were evaluated for rigor, credibility, and relevance. Firstly, rigor refers to whether the research method used is appropriate. Reliability refers to whether the findings are valid and meaningful and whether the study method is reliable. Relevance is whether the findings are relevant to the hospitality industry. Evaluation of the articles in terms of the specified criteria narrowed the final sample to 18 studies (as shown in Figure 1).

The final phase of the research was concerned with data analysis and synthesis. With deductive content analysis, each study was reviewed independently by two separate authors and data were extracted, including study design, sample, study setting, outcome variables, and implications. A concept matrix was developed to synthesize the findings. Studies were analyzed by considering factors that enabled or hindered AI adoption, the type of AI used, and the impact of AI on hospitality employee outcomes. Figure 1 presents a flowchart of the search process.

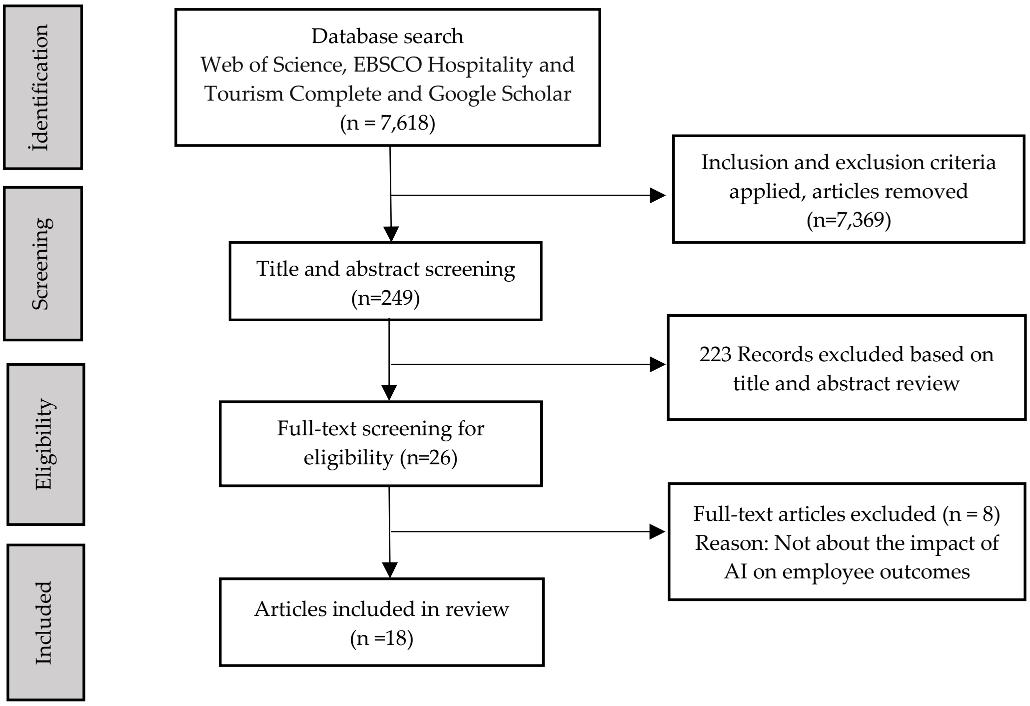

Figure 1. *PRISMA flowchart*

RESULTS

Descriptive analysis

This section provides descriptive information such as the distribution of selected studies by journals, years, and countries, and the study context, participants, method, and purpose of the study.

Article Distribution across Academic Journals

Table 2 shows the distribution of articles by journals. Of the 18 journal articles, 13 were related to tourism and hospitality journals, while 5 were related to tourism and non-hotel journals. The largest number of AI articles is found in the International Journal of Contemporary Hospitality Management (n=4), followed by International Journal of Hospitality Management (n=2), Tourism Management (n=2) and Technology in Society (n=2). The rest of the publications are dispersed among different journals. In terms of publishers, 18 peer-reviewed journal articles in the field of AI have been published in well-known academic databases such as Elsevier, Emerald and Taylor & Francis.

Table 2. *Distribution of articles*

Journals	**Publishers**	**Number of articles**
International Journal of Contemporary Hospitality Management	Emerald Group Publishing	4
International Journal of Hospitality Management	Elsevier	2
Tourism Management	Elsevier	2
Technology in Society	Elsevier	2
Journal of Hospitality Marketing & Management	Taylor and Francis Online	1
British Journal of Management	John Wiley & Sons, Inc.	1
Current Issues in Tourism	Taylor and Francis Online	1
Frontiers in Psychology	Frontiers Media S.A.	1
Journal of Sustainable Tourism	Taylor and Francis Online	1
Tourism Management Perspectives	Science Direct	1
Journal of Hospitality and Tourism Technology	Emerald Insight	1
Journal of Service Theory and Practice	Emerald Group Publishing	1
Total		18

Overview of Studies

The results indicate that the included articles have been conducted across a range of different countries and diverse hospitality and tourism contexts. All the articles in our sample covered a period of the last two years. The majority of the research related to AI was conducted in China (n=10), followed by USA (n=2), Vietnam (n=1), Pakistan (n=1), Turkey (n=1), and Portugal (n=1). In terms of study context, the vast majority of research was conducted on employees from the accommodation industry (n=15), followed by employees from the restaurant industry (n=1) and a mix of accommodation and restaurant industry (n=2). Further, various research methods have been used in AI research. The findings of this review show that a vast majority of the papers are quantitative (n=11). There were two qualitative studies and three mixed methods. Additionally, there were one conceptual and one-literature review articles, as shown in Table 3.

Table 3. *Overview of studies involved in the SLR*

#	Author (year), country	Study context	Participants	Methodology	Study objective
1	Kong et al. (2021), China	Hospitality industry	Employees (n=432)	Quantitative	To assess the effect of AI on hospitality employees from a career perspective.
2	Prentice et al. (2019), Portugal	Hospitality industry	Employees (n=60 hotels)	Quantitative	To discover the impact of AI and emotional intelligence on performance and employee retention.
3	Li et al. (2019), China	Hospitality industry	Employees (n=468)	Quantitative	To determine the impact of AI and robotic awareness on hotel employees' turnover intention.

4	Ding (2021), USA	Service Industry	Employees (n=190)	Quantitative	To determine the relationship between employees' challenge-hindrance appraisals of smart technology, AI, robotics, and algorithms and individual competitive productivity.
5	Koo et al. (2021), USA	Hospitality	Employees (n=425)	Mixed Methods	To determine the impact of AI on hospitality employees with a pragmatic approach, taking into account job insecurity.
6	Qiu et al. (2020), China	Hospitality	Employees and supervisors (n=342)	Quantitative	To determine how AI empowers hospitality employees physically, mentally, and emotionally.
7	Nguyen and Malik (2021), Vietnam	Hospitality	Employees and managers (n=313)	Quantitative	To explore the effect of AI on employees' perception of AI service and job satisfaction.
8	Zhao et al. (2022), China	Hospitality	Employees (n=358)	Mixed Methods	To explore the impact of AI surveillance on employee engagement.
9	Wang et al. (2022), China	Hospitality	Employees (n=264)	Quantitative	To determine the effect of AI and robotic awareness on employee creativity.
10	Rydzik and Kissoon (2021)	Hospitality and tourism	Employees	Conceptual	To discuss the effects of technological transformations on low-paid and low-skilled tourism employees.
11	Fu et al. (2022), China	Hospitality	Employees (n=19)	Qualitative	To examine the challenges of robots and to determine their effect on hospitality employees.
12	Yu et al. (2022), China	Hospitality	Employees (n=281)	Quantitative	To identify the relationships between employees' technology knowledge, social skills and transformational leadership through service robot risk awareness.
13	Khaliq et al. (2022), Pakistan	Hospitality	Employees and managers (n=330)	Quantitative	To explore the association between turnover intention and AI and robotics awareness.
14	Vatan and Dogan (2021), Turkey	Hospitality	Employees (n=40)	Qualitative	To investigate the perceptions of Turkish hospitality employees towards service robots.
15	Zhong et al. (2022), China	Hospitality	Multiple perspectives including employees (n=142)	Mixed method	To determine the perspectives of urban hotel guests, managers and staff on the effects of service robots.
16	Liang et al. (2022), China	Service Industry	Multiple perspectives including hotel and restaurant employees (n=317)	Quantitative	To reveal the association between service innovative behavior and AI awareness.
17	Wu et al. (2022), China	Hospitality	Employees and managers (n=454)	Quantitative	To shed light on the consequences of technostress on employees.
18	Lu et al. (2020)	Service Industry	Multiple perspectives including employees	Literature Review	To manage a literature review on the effect of robots on employees and customers.

Deductive Content Analysis

This section shows the deductive content analysis based on our SLR. Deductive content analysis is often based on previous work such as theories and literature reviews, and a structured analysis matrix can be used for the purpose of the study (Kyngäs & Vanhanen, 1999). Three major themes were identified during the analysis process: (i) enablers or inhibitors of AI adoption (factors that enable or inhibit the employ of AI technologies in the workplace); (ii) the type of AI-related technique (what type of AI technology is used in organizations); (iii) outcomes of AI adoption (employees' work outcomes of using AI in the workplace). This discussion generates knowledge and understanding of how hospitality industry use AI, the enablers or inhibitors of AI adoption, and the impact of AI on employees' work outcomes. Table 4 presents the themes identified as a result of the analysis process.

Table 4. *Summary of the findings*

#	Enablers or inhibitors of AI adoption	The type of AI-related technique	Outcomes	Main findings and implications
1	Top management support	AI in general	Job burnout, Low organizational commitment	AI awareness is linked to high job burnout. In addition, AI awareness negatively affects the organizational commitment of hospitality employees. Managers should provide support to employees and motivate them to collaborate with AI to overcome the negative effects of AI on employees.
2	N/A	AI in general	High job performance	While AI plays an important role in job performance, it negatively impacts employee job efficiency and customer satisfaction. This points out that AI acts as a buffer on job performance.
3	Top management support, Knowledge about AI	AI in general, Robots	Turnover intention	AI and robotic awareness are linked to employee turnover intention. Organizational support weakens employees' intention to leave. Hotels should develop regularly planned and long-term training programs to keep employees up-to-date on new practices and develop new skills.
4	Top management support, Knowledge about AI,	AI in general, robots	Low job engagement, Low organizational Commitment	STARA awareness hinders employees' organizational commitment and engagement. Managers should provide support and training so that employees can adapt to the changing working environment, work with developing technologies, and adopt these technologies. Thus, employees can learn new skills and develop competencies to work in harmony with emerging technology.
5	Top management support, Knowledge about AI	AI in general, Robots	Low job engagement, Turnover intention	AI technologies activate employees' perceptions of job insecurity. And perceived job insecurity significantly reduces employee engagement and indirectly influences turnover intention. In today's technology world, hospitality workers must acquire skills in line with the emerging technology and the hospitality industry should continue to support employees.
6	Top management support	AI in general, Robots	High well-being	Service attributes associated with AI importantly reduce employee physical and mental fatigue and increase their positive emotions. Hospitality businesses can create a supportive work environment for employees by taking into account their well-being and helping them maintain their good feelings.
7	N/A	AI in general	High job satisfaction	The service quality perception of the AI application affects hospitality employees' job satisfaction.

8	Top management support, Knowledge about AI	AI in general	Job engagement	AI surveillance affects job engagement. Supervisor and coworker support has a stronger impact on employees when AI surveillance is low.
9	Knowledge about AI, Readiness to use AI,	AI in general, Robots	Employee creativity	AI and Robotics Awareness (AIRA) positively influences employee creativity. Before adopting AI and robotics, organizations should be ready for change, explain the changes brought by the emerging technology to their employees. Further, trainings should be prepared to help employees develop themselves and acquire new knowledge and skills.
10	Readiness to use AI, Knowledge about AI	Intelligent automation	Low well-being	The expansion of smart automation in tourism industry can increase inequalities among employees, cause job losses, make them insecure, and consequently negatively affect their well-being.
11	Knowledge about AI	Robot (service robot)	Burnout (emotional exhaustion)	Excessive workload of service robots causes exhaustion in employees. Employees need to develop some skills to avoid the negative effect of emerging technologies.
12	Knowledge about AI	Robot (service robot)	Turnover intention	Service robot risk awareness is positively associated with turnover intention. Employees with high technological and interpersonal skills have less risk awareness towards service robots.
13	Knowledge about AI	AI in general, Robots	Turnover intention	AI and robotics awareness positively affects employees' turnover intention. To take advantage of AI and emerging technology, employees need to develop their skills and be trained regularly.
14	N/A	Robot (service robot)	Low job satisfaction, Low organizational commitment	Employees' attitudes towards service robots are that it causes unemployment, low organizational commitment and low job satisfaction.
15	Knowledge about AI	Robot (service robot)	High well-being	From an employee perspective, robots benefit employees and increase their well-being. As employees increase their skills, their resistance to the adoption of AI and robots decreases.
16	Top management support, Knowledge about AI	AI in general	Burnout (emotional exhaustion)	AI awareness causes emotional exhaustion that can hinder employees' innovative service behaviors. An environment should be created that will enable employees to adapt their skills according to the emerging technology and training programs should be organized.
17	Top management support, Knowledge about AI	AI in general, Big data analytics	Low job performance, Low employee engagement and Well-being	Technostress reduces employee performance, engagement and well-being. In order for employees to have technology-related skills, managers must provide them with the necessary training and support.
18	Knowledge about AI	Robots (Service robots)	High job satisfaction	Although service robots cause a number of negative psychological consequences such as job insecurity and loss of autonomy, they also provide benefits such as increased productivity and job satisfaction. Organizations should equip their employees with robotic skills in order to adapt to emerging technology.

Enablers or Inhibitors of AI Adoption

The factors suggested in the literature that may enable or inhibit AI adoption are divided into three distinct categories including readiness to use AI, knowledge about AI and top management support. This section discusses in detail the factors that enable or inhibit the AI adoption.

Readiness to use AI: It's about being ready to use the applications and changes that AI brings to organizations (Alsheibani et al., 2018). If organizations are not ready to use emerging technologies such as AI and robotics, employees will feel constrained by new technologies and the benefits of technology will not be noticed by them (Chatterjee et al., 2021). Iacovou et al. (1995) defines organizational readiness as the availability of organizational resources necessary for the adoption of change. Organizational readiness includes technological and financial resources, culture and lack of skills, and the human factor in general (Dasgupta & Wendler, 2019). Thus, higher readiness for innovation increases the success of innovation while reducing the risk of failure (Snyder-Halpern, 2001).

Knowledge about AI: Emerging technologies like AI requires employees to develop certain skills to ensure organizational effectiveness (Behl et al., 2021). Developing skills related to AI technologies is also crucial to helping employees get employed in the future (Jaiswal et al., 2022). Softer intuitive and empathetic skills benefit service employees to adapt to emerging technologies such as AI (Huang & Rust, 2018). Therefore, organizations are recommended to organize training for their front-line service employees to develop AI skills (Fountaine et al., 2019).

Top management support: This is about top management recognizing the importance of adopting technology (Garcia-Morales et al, 2014). Alsheibani et al. (2020) state that management support is a key driver for AI adoption. On the other hand, lack of support causes organizations not only to fail to adopt innovation but also to lose a competitive advantage (Wade & Hulland, 2004).

The Type of AI-Related Technique

This section demonstrates a review and integration of the type of AI that selected articles focus on. Published literature presented in this paper show can be evaluated in four categories: AI (general), robot, big data analytics and intelligent automation.

AI (general): According to Huang and Rust (2018), there are four types of artificial intelligence namely mechanical, analytical, intuitive and empathetic. Mechanical AI is about performing routine and repetitive tasks automatically and is based on observation. Analytical AI is about processing information to find solutions to problems and learn from past experiences. Intuitive AI is about creative thinking and the ability to adapt effectively to new situations and includes skills that require insight and creative problem solving. Finally, empathic AI often involves emotionally responsive machines that recognize and understand emotions like a human (e.g. Robot Sophia).

Robot: A robot is defined as "an autonomous system which exists in the physical world, can sense its environment, and can act on it to achieve some goals" (Matarić, 2007, p.2). Robots are divided into two as service robots and industrial robots. Industrial robots perform tasks such as welding and palletizing in manufacturing and production, while service robots are used to assist and serve humans (Ivanov et al., 2017). Service robots, supported by AI technologies and able to communicate with humans, are mostly used in room service, entertainment and front office operations of hospitality industry (Lukanova & Ilieva, 2019).

Big data analytics: This refers to the techniques utilized to analyze big data and derive intelligence from it (Gandomi & Haider, 2015). It aims to provide new insights that complement traditional statistics, archival data sources and surveys in meaningful and often real time (Xiang et al., 2015). Big data on tourism and hospitality is divided into three: UGC data generated by users, device data, and transaction data (Li et al., 2018).

Intelligent automation: This refers to the application of emerging technologies, including AI, robotics and the internet of things, to provide services without the need for humans in tourism environments (Tussyadiah, 2020). Some hotels implement intelligent automation for customer-based services, while others work almost entirely with robots. For example, an AI robot named Connie has been implemented by the Hilton group. The robot can interact with customers and provide tourist information (Konstantinova, 2019).

Outcomes of AI Adoption

Based on the findings on the impact of AI on employees' work outcomes, two major categories of employee outcomes were identified, including attitudinal and behavioral outcomes. The variables in the first category are well-being, turnover intention, job engagement, organizational commitment, burnout, and job satisfaction, whereas the variables in the second category consist of job performance and creativity (see Table 3 and Figure 2).

Attitudinal Outcomes. This section provides a review and discussion of the five attitudinal outcomes determined in this study: well-being, turnover intention, organizational commitment, burnout, job satisfaction, and job engagement.

Well-being: Well-being was the most frequently researched outcome (n=4). Half of the articles in this subgroup (n=2) state that AI causes low employee well-being, while the other half argues that it increases employee well-being (n=2). With the emergence of new technologies, changes in organizations may affect the well-being of employees by changing processes, tasks and structures in the organization (Nazareno & Schiff, 2021). Employment is an important part of an individual's overall sense of security and well-being (Yan et al., 2022). Considering that AI applications in organizations may lead to a perception of job insecurity among employees (Koo et al., 2021), it is possible to say that job insecurity may negatively affect the well-being of employees (Lingmont & Alexiou, 2020).

Turnover intention: Another most frequently examined employee outcome was employees' intention to leave their work (n=4). Although AI is part of innovation in the hospitality sector, it can threaten people's jobs due to its ability to copy the human thought process (Koo et al., 2021). Emerging technologies have led to turnover intention and employment uncertainty among hospitality employees (Khaliq et al., 2022). Moreover, Li et al. (2019) determined that the changes caused by new technologies such as AI create a perception of job insecurity and, as a result, have an effect on employee turnover intention.

Job engagement: AI impacts on job engagement was examined in four of the studies. AI has a great opportunity and the ability to create change in employee engagement (Agarwal et al., 2021). However, Ding (2021) found a significant negative association between employee' STARA awareness and their job engagement. Another study in the sample (Koo et al., 2021) discovered that perceived job insecurity resulting from AI technologies reduces job engagement. The study by Wu et al. (2022) found that technostress caused by the use of emerging technologies negatively affects job engagement. Zhao et al. (2022) revealed that AI surveillance has a moderating role in the association between social support and job engagement.

Organizational commitment: Of the 18 empirical studies reviewed, 3 measure the impact of AI on organizational commitment. These studies conclude that AI and robotic technologies negatively affect employee organizational commitment. The human touch is important in services, especially in the hospitality industry (Saini & Bhalla, 2022). Thus, AI integration can disrupt the relationship between employees and organizations (Kong et al., 2021), cause psychological damage to employees, and negatively affect their sense of belonging and commitment to the workplace (Li et al., 2019).

Burnout: AI impact on burnout was examined in three empirical studies in the sample and a negative relationship was found. Although some tasks in organizations, such as employee orientation and training, are still the responsibility of humans, AI systems perform many activities such as recruitment, training, evaluation and monitoring and control (Tschang & Almirall, 2021). Supervisor robots also have the authority to give negative feedback to human employees. Human employees are also likely to perceive these feedbacks as offensive and abusive (Yam et al., 2022). Therefore, employees with a high awareness of AI may perceive uncertainty about their careers, which can lead to burnout (Kong et al., 2021).

Job satisfaction: The findings from three studies demonstrated that AI was associated with job satisfaction. An empirical study found that high-quality AI service was positively associated with job satisfaction of hospitality employees (Nguyen & Malik, 2021). On the other hand, Vatan and Dogan (2021) found that service robots may cause unemployment and low job satisfaction. Specifically, a robot can learn the characteristics of employees that cause work efficiency differences throughout the workday and help facilitate that employee's tasks (Bowen & Morosan, 2018). Collaboration between employees and robots can drive service improvement by increasing employees’ satisfaction levels (Qiu et al., 2020).

Behavioral Outcomes. This section provides a general overview of two behavioral outcomes: job performance and creativity.

Job performance: The effect of AI on job performance was highlighted in the results of 2 of the 18 studies. AI and robotic technology may help the hospitality industry to strengthen service quality and improve job performance (Ivanov et al., 2017). The study of Prentice et al. (2019) also points out that providing services using AI positively affects job performance of hospitality employees. However, one study in the sample revealed that role overload caused by AI technologies can increase technostress among employees and weaken their job performance (Wu et al., 2022).

Creativity: A very few articles (n=1) linked AI and employee creativity. Employees' creativity in the hospitality industry has become a competitive advantage. In general, creativity in the hospitality industry focuses on using creative ideas to ensure customer satisfaction and improve service quality (Li et al., 2018). AI enhances employee skills by enhancing their job learning, allows them to engage in creativity and innovation in their work by preventing them from wasting time on mundane tasks (Malik et al., 2022). As Wang et al. (2022) reveal, hospitality employees' awareness of AI and robotics benefits their creativity.

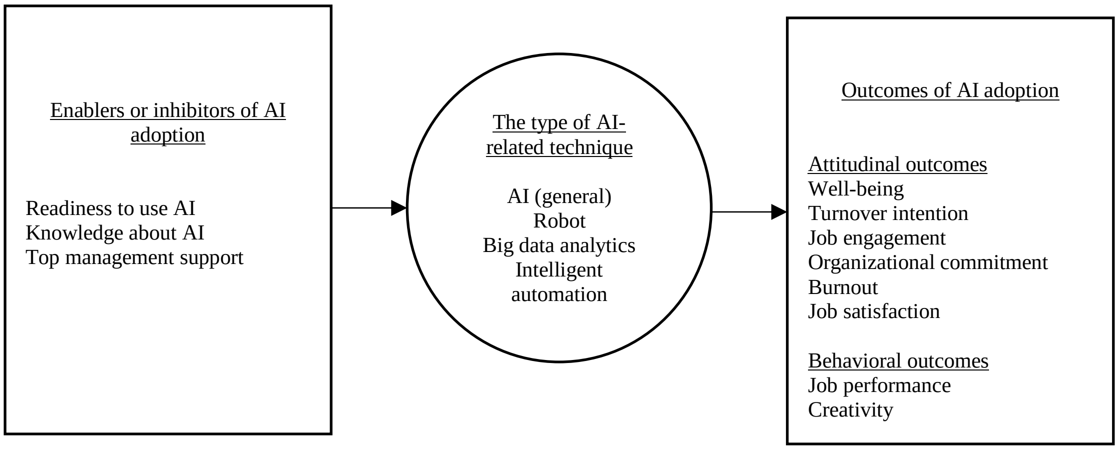

Figure 2. *The conceptual framework of AI adoption*

DISCUSSION AND CONCLUSION

The current paper systematically synthesized the relationship between AI and employee work outcomes in the hospitality context. The results of our review consist of three parts (see Fig. 2). First, some enablers and inhibitors of AI adoption are discovered. The antecedents of AI adoption include readiness to use AI, knowledge about AI, and top management support. Agarwal et al. (2021) states that change is an inevitable part of organizations and organizations should be ready to use technological innovations in order to gain competitive advantage and sustainability. Our review also indicates that the adoption and successful implementation of AI in organizations requires certain skills. These findings are also compatible with organizational change theory, which argues that some preparations such as explaining the necessity of change to employees, mobilizing them to support change, developing skills suitable for change and creating a culture that supports change will enable organizations to achieve positive results (Battilana et al., 2010). On the other hand, as with every change, the changes caused by emerging technologies also encounter resistance (Agarwal et al. 2021). At this point, our review has shown that top management support plays an important role in the adoption of emerging technologies such as

AI. This finding is consistent with the view advocating that leaders should use effective communication and develop a vision that will increase employee motivation in the face of resistance to change (Page & Schoder, 2018). Second, AI-related techniques and applications have been evaluated in four categories in the published literature: AI, robotics, big data analytics and intelligent automation. Finally, the impacts of AI on employee work outcomes were categorized as behavioral and attitudinal outcomes, highlighted eight outcomes that were consistently investigated: well-being, turnover intention, job engagement, organizational commitment, burnout, job satisfaction, job performance and creativity. Furthermore, our review presents significant theoretical and practical implications, as follows.

Theoretical Implications

Providing a novel conceptual framework of AI adoption (Fig. 2), this research makes some contributions to the hospitality literature by drawing attention to the antecedents of AI adoption and employee work outcomes. First, to the best of our knowledge, this paper is the first systematic review to investigate the effect of AI on employee outcomes in the hospitality industry. The majority of prior and existing research has evaluated AI from the customer's perspective (Prentice et al., 2020; Li et al., 2022). Second, we used deductive content analysis along the logic of "enablers or inhibitors of AI adoption, type of AI-related technique and outcomes" that allows us to highlight the process of AI impacts in the workplace. Our analysis results reveal the antecedents affecting AI adoption in the workplace and the positive or negative employee outcomes of AI implementation. Thus, these results provide a solid basis for future research in the hospitality field examining the adoption or effects of AI in the workplace.

Practical Implications

Our SLR provides highlights some managerial implications for hospitality practitioners. This study shows that the impact of AI on employee work outcomes can be influenced through various antecedents. First, this review highlights the role of readiness to use AI in driving positive employee business outcomes. Therefore, developing strategies and preparations for technology adoption and implementation can help organizations successfully manage the process. As a matter of fact, organizational change theory states that being ready for organizational change has a critical importance in the success of change initiatives (Choi & Ruona, 2011). Second, this review reveals the importance of knowledge about AI. Given that employees need to develop skills appropriate to AI and robotics technologies (Behl et al., 2021), it is critical for organizations to organize training for new skills at all levels. Lastly, this review emphasizes that the influence of top management support in this process. From the employee perspective, a supportive approach should be adopted about the opportunities that emerging technologies such as AI will offer to employees, and an innovative culture should be created that encourages them to take risks and embrace change. AI-powered technologies require employees to think systems-oriented, design-oriented, enhancing creativity, and make decisions based on data (Jaiswal et al., 2022). Hence, management support is critical in encouraging employees to develop skills for AI-powered technologies.

Limitations and Future Research

This SLR has several limitations. First, this review only focused on peer-reviewed English articles published in high-quality journals. There are academic studies in other languages that contain rich contextual information. Future review studies can further research the consequences of AI by including studies published in different languages. Second, this SLR do not include non-indexed journals, dissertations, or conference papers as they did not meet our predefined inclusion criteria. Therefore, more studies can be conducted that include other types of studies and that can discuss or enrich the existing findings on the effect of AI on employee work outcomes.

REFERENCES

Agarwal, M., Yadav, A., & Kumar Sharma, S. (2021). Role of artificial intelligence on job engagement and employee behavior in an organization. Paper presented at the *International Conference on Embracing Change & Transformation-Breakthrough Innovation and Creativity*, 23-25 March.

Alansari, H., Gerwe, O., & Razzaque, A. (2021). Role of artificial intelligence during the Covid-19 Era. In A. Musleh Al-Sartawi (Ed.), *The Big Data-Driven Digital Economy: Artificial and Computational Intelligence* (pp. 157-173). Springer Nature, Cham, Switzerland.

Al-Haddad, S., & Kotnour, T. (2015). Integrating the organizational change literature: A model for successful change. *Journal of Organizational Change Management*, *28*(2), 234-262.

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial intelligence adoption: AI-readiness at firm-level. *PACIS Proceedings*, 37.

Alsheibani, S., Messom, C., & Cheung, Y. (2020). Re-thinking the competitive landscape of artificial intelligence. Paper presented at the Proceedings of the 53rd Hawaii international conference on system sciences.

Armenakis, A.A., & Bedeian, A.G. (1999). Organizational change: a review of theory and research in the 1990s. *Journal of Management*, *25*(3), 293-315.

Battilana, J., Gilmartin, M., Sengul, M., Pache, A.C., & Alexander, J.A. (2010). Leadership competencies for implementing planned organizational change. *The Leadership Quarterly*, *21*(3), 422-438.

Behl, A., Chavan, M., Jain, K., Sharma, I., Pereira, V.E., & Zhang, J.Z. (2021). The role of organizational culture and voluntariness in the adoption of artificial intelligence for disaster relief operations. *International Journal of Manpower*, *43*(2), 569-586.

Borges, A.F.S., Laurindo, F.J.B., Spínola, M.M., Gonçalves, R.F., & Mattos, C.A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, 102225.

Bowen, J., & Morosan, C. (2018). Beware hospitality industry: The robots are coming. *Worldwide Hospitality and Tourism Themes*, *10*(6), 726-733.

Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust". *Journal of Business Research*, *131*, 485-494.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management and Organization*, *24*(2), 239-257.

Budhwar, P., Malik, A., De Silva, M.T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management*, *33*(6), 1065-1097.

Castellacci, F., & Viñas-Bardolet, C. (2019). Internet use and job satisfaction. *Computers in Human Behavior*, *90*, 141–152.

Chatterjee, S., Rana, N.P., Dwivedi, Y.K., & Baabdullah, A.M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting & Social Change*, *170*, 120880.

Choi, M., & Ruona, W. E. A. (2011). Individual readiness for organizational change and its implications for human resource and organization development. *Human Resource Development Review*, *10*(1), 46-73.

Cohen, S. G., & Bailey, D. E. (1997). What makes teams work: Group effectiveness research from the shop floor to the executive suite. *Journal of Management*, *23*(3), 39-290.

Dasgupta, A., & Wendler, S. (2019). AI adoption strategies. Retrieved September 18, 2022 from https://www.ctga.ox.ac.uk/files/aiadoptionstrategies-march2019.pdf

Ding, L. (2021). Employees' challenge-hindrance appraisals toward STARA awareness and competitive productivity: A micro-level case. *International Journal of Contemporary Hospitality Management*, *33*(9), 2950-2969.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*, *97*(4), 62-73.

Friday, E., & Friday, S.S. (2003). Managing diversity using a strategic planned change approach. *Journal of Management Development, 22*(10), 863-880.

Fu, C.J., & Cheng, C.I. (2014). Unfulfilled expectations and promises, and behavioral outcomes. *International Journal of Organizational Analysis*, *22*(1), 61-75.

Fu, S., Zheng, X., & Wong, I.A. (2022). The perils of hotel technology: The robot usage resistance model. *International Journal of Hospitality Management*, 102, 103174.

Fung, H. P. (2014). Relationships among team trust, team cohesion, team satisfaction, team effectiveness and project performance as perceived by project managers in Malaysia. *Australian Journal of Basic and Applied Sciences*, *8*(8), 205-216.

Gandomi, A., & Haider, M. (2015). Beyond the hype: big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137-144.

Garcia-Morales, V. J., Bolivar-Ramos, M. T., & Martin-Rojas, R. (2014). Technological variables and absorptive capacity's influence on performance through corporate entrepreneurship. *Journal of Business Research*, *67*(7), 1468–1477.

Hassan, A.T. (2018). Organizational change management: A literature review. *SSRN Electronic Journal*. https://dx.doi.org/10.2139/ssrn.3135770

Hirschi, A. (2018). The Fourth Industrial Revolution: Issues and implications for career research and practice. *Career Development Quarterly*, *66(*3), 192-204.

Huang, A., Chao, Y., de la Mora Velasco, E., Bilgihan, A., & Wei, W. (2022). When artificial intelligence meets the hospitality and tourism industry: An assessment framework to inform theory and management. *Journal of Hospitality and Tourism Insights*, *5*(5), 1080-1100.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155-172.

Iacovou, C.L., Benbasat, I., & Dexter, A.S. (1995). Electronic data interchange and small organizations: adoption and impact of technology. *MIS Quarterly*, *19*(4), 465-85.

Ivanov, S. H., Webster, C., & Berezina, K. (2017). Adoption of robots and service automation by tourism and hospitality companies. *Revista Turismo & Desenvolvimento*, *27*(28), 1501-1517.

Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: upskilling for artificial intelligence in multinational corporations. *The International Journal of Human Resource Management*, *33*(6), 1179-1208.

Judge, A. T., Cable, D. M., Colbert, A. E., & Rynes, S. L. (2007). What causes a management article to be cited—Article, author, or journal?. *Academy of Management Journal*, 50(3), 491-506.

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, Article 134120.

Khaliq, A., Waqas, A., Nisar, Q. A., Haider, S., & Asghar, Z. (2022). Application of AI and robotics in hospitality sector: A resource gain and resource loss perspective. *Technology in Society*, *68*, 101807.

Kitchenham, B. (2004). Procedures for performing systematic reviews. *Keele, UK, Keele University Technical Report*, 33, 1-26.

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, *33*(2), 717-734.

Konstantinova, S. (2019). Digital transformation in tourism knowledge. *International Journal*, *35*(1), 188-193.

Koo, B., Curtis, C., & Ryan, B. (2021). Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *International Journal of Hospitality Management*, 102763.

Kopka, A., & Grashof, N. (2022). Artificial intelligence: Catalyst or barrier on the path to sustainability? *Technological Forecasting Social Chang*e, *175*, 121318.

Kyngäs, H., & Vanhanen, L. (1999). Content analysis (Finnish). *Hoitotiede, 11*, 3–12.

Latah, M., & Toker, L. (2018). Artificial intelligence enabled software-defined networking: A comprehensive overview. *IET Networks*, *8*(2), 79–99. https://doi.org/10.1049/iet-net.2018.5082.

Lee, T. T. (2006). Adopting a personal digital assistant system: Application of Lewin's change theory. *Journal of Advanced Nursing, 55*, 487–496.

Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging technology and business model innovation: the case of artificial intelligence. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*(3), 44.

Lewin, K. (1951). *Field theory and social science*. New York: Harper and Brothers.

Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism Management*, *68*, 301-323.

Li, J.J., Bonn, M.A., & Ye, B.H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management*, *73*, 172-181.

Li, M., Yin, D. and Qiu, H., & Bai, B. (2022). Examining the effects of AI contactless services on customer psychological safety, perceived value, and hospitality service quality during the COVID-19 pandemic. *Journal of Hospitality Marketing & Management*, *31*(1), 24-48.

Liang, X., Guo, G., Shu, L., Gong, Q., & Luo, P. (2022). Investigating the double-edged sword effect of AI awareness on employee's service innovative behavior. *Tourism Management*, 92, 104564.

Lingmont, D.N.J., & Alexiou, A. (2020). The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change*, *161*, 120302.

Lu, V.N., Wirtz, J., Kunz, W.H., Paluch, S., Gruber, T., Martins, A., & Patterson, P.G. (2020). Service robots, customers and service employees: what can we learn from the academic literature and where are the gaps?. *Journal of Service Theory and Practice*, 30(3), 361-391.

Lukanova, G., & Ilieva, G. (2019). Robots, artificial intelligence, and service automation in hotels. In S. Ivanov & C. Webster (Eds.), *Robots, artificial intelligence, and service automation in travel, tourism and hospitality* (pp. 157-183). Emerald Publishing Limited, Bingley.

Malik, N., Tripathi, S.N., Kar, A.K., & Gupta, S. (2022). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower, 43*(2), 334-354.

Matarić, M.J. (2007). *The robotics primer.* Massachusetts Institute of Technology, Mit Press.

McCarthy, J. (2007). What is artificial intelligence? Retrieved October 12, 2022, from http://jmc.stanford.edu/articles/ whatisai/whatisai.pdf

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434.

Nam, K., Dutt, C. S., Chathoth, P., Daghfous, A., & Khan, M. S. (2021). The adoption of artificial intelligence and robotics in the hotel industry: Prospects and challenges. *Electronic Markets*, *31*, 553-574.

Nazareno, L., & Schiff, D.S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technol. Soc*., *67*, 101679.

Nguyen, T.M., & Malik, A. (2021). A two-wave cross-lagged study on AI service quality: The moderating effects of job role. *British Journal of Management*, *33*(3), 1221-1237.

Page, L., & Schoder, J. (2018). Making change last: leadership is the key. *Journal of Business Strategy*, *40*(2), 32-41. doi.org/10.1108/JBS-01-2018-0003

Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review*, *33*(1), 100857.

Prentice, C., Lopes, S.D., & Wang, X. (2019). Emotional intelligence or artificial intelligence: an employee perspective. *Journal of Hospitality Marketing & Management*, *29*(4), 377-403.

Prentice, C., Lopes, S.D., & Wang, X. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. *Journal of Hospitality Marketing & Management*, *29*(7), 739-756.

Qiu, H., Yu, D., Ye, S., Shan, R., Ai, J., & Shi, J. (2020). Long-term oncological outcomes in robotic versus laparoscopic approach for rectal cancer: a systematic review and meta-analysis. *Int J Surg*, *80*, 225-230.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, *46*(1), 192-210. 10.5465/2018.0072

Ruel, H., & Njoku, E. (2021). AI redefining the hospitality industry. *Journal of Tourism Futures*, *7*, 53-66.

Rydzik, A., & Kissoon, C.S. (2021). Decent work and tourism workers in the age of intelligent automation and digital surveillance. *Journal of Sustainable Tourism*, 30(12), 2860-2877.

Saini, A., & Bhalla, R. (2022). Artificial intelligence and automation: transforming the hospitality industry or threat to human touch. In V. Garg & R. Goel (Eds.), *Handbook of research on innovative management using AI in industry* 5.0 (pp. 88-97). IGI Global.

Samala, N., Katkam, B. S., Bellamkonda, R. S., & Rodriguez, R. V. (2020). Impact of AI and robotics in the tourism sector: A critical insight. *Journal of Tourism Futures*, *8*(1), 73-87.

Snyder-Halpern, R. (2001). Indicators of organizational readiness for clinical information technology/systems innovation: A Delphi study. *International Journal of Medical Informatics*, *63*, 179-204.

Tschang, F. T., & Almirall, E. (2021). Artificial intelligence as augmenting automation: Implications for employment. *Academy of Management Perspectives*, *35*(4), 642-659.

Tussyadiah, I. (2020). A review of research into automation in tourism: launching the annals of tourism research curated collection on artificial intelligence and robotics in tourism. *Annals of Tourism Research*, *81*, 102883.

Úbeda-García, M., Claver-Cortés, E., Marco-Lajara, B., García-Lillo, F., & Zaragoza-Sáez, P.C. (2018). Continuous innovation in the hotel industry: The development of organizational ambidexterity through human capital and organizational culture in Spanish hotels. *International Journal of Contemporary Hospitality Management*, *30*(12), 3609-3631.

Vatan, A., & Dogan, S. (2021). What do hotel employees think about service robots? A qualitative study in Turkey. *Tourism Management Perspectives*, *37*(1), 100775.

Vial, G. (2019). Understanding digital transformation: a review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118-144.

Wade, M., & Hulland, J. (2004). Review: the resource-based view and information systems research: review, extension, and suggestions for future research. *MIS Quarterly*, *28*(1), 107-142.

Wang, H., Zhang, H., Chen, Z., Zhu, J., & Zhang, Y. (2022). Influence of artificial intelligence and robotics awareness on employee creativity in the hotel industry. *Frontiers in Psychology*, *13*, 1-12.

Wilkens, U. (2020). Artificial intelligence in the workplace–A double-edged sword. *The International Journal of Information and Learning Technology*, *37*(5), 253-265.

Wirtz, B.W., Weyerer, J.C., & Geyer, C. (2019). Artificial intelligence and the public sector. Applications and challenges. *International Journal of Public Administration*, *42*(7), 596-615.

Wright, S., & Schultz, A. (2018). The rising tide of artificial intelligence and business automation: developing an ethical framework. *Business Horizons*, *61*, 823-832.

Wu, W., Chin, W., & Liu, Y. (2022). Technostress and the smart hospitality employee. *Journal of Hospitality and Tourism Technology*, *13*(3), 404-426.

Xiang, Z., Schwartz, Z., Gerdes, J., & Uysal, M. (2015). What can big data and text analytics tell us about hotel guest experience and satisfaction?. *International Journal of Hospitality Management*, *44*, 120-130.

Yam, K.C., Goh, E.Y., Fehr, R., Lee, R., Soh, H., & Gray, K. (2022). When your boss is a robot: Workers are more spiteful to robot supervisors that seem more human. *Journal of Experimental Social Psychology*, *102*, 104360.

Yan, H. Fu, L., & Hu, X. (2022). Harnessing service robots to increase frontline service employees' safety and health: The critical role of CSR. *Safety Science, 1151*, 105731.

Yang, J., & Chew, E. (2021). A systematic review for service humanoid robotics model in hospitality. *International Journal of Social Robotics, 13*, 1397-1410.

Yu, H., Shum, C., Alcorn, M., Sun, J., & He, Z. (2022). Robots can't take my job: antecedents and outcomes of gen Z employees' service robot risk awareness. *International Journal of Contemporary Hospitality Management*, *34*(8), 2971-2988.

Yu, X., Xu, S., & Ashton, M. (2023). Antecedents and outcomes of artificial intelligence adoption and application in the workplace: The socio-technical system theory perspective. *Information Technology and People*, *36*(1), 454-474.

Zhao, H., Lan, J., Lyu, T., & Zeng, G. (2022). Working with artificial intelligence surveillance during the COVID-19 pandemic: A mixed investigation of the influence mechanism on job engagement in hospitality industry. *Current Issues in Tourism*, https://doi.org/10.1080/13683500.2022.2117593.

Zhong, L., Verma, R., Wei, W., Morrsion, A.M., & Yang, L. (2022). Multi-stakeholder perspectives on the impacts of service robots in urban hotel rooms. *Technology in Society*, 68, 101846.

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RESEARCH TO DETERMINE THE POTENTIAL USE OF HUMANOID (ANTHROPOMORPHIC) ROBOTS IN ACCOMMODATION FACILITIES

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ABSTRACT

Study participants evaluated the use of robots in general, and specifically the use of humanoid robots for 36 different job positions in accommodation establishments in Turkey. This exploratory study aimed to determine the positions in which it will be easier to adopt the use of robots in accommodation businesses. It also examined the role of the participant's gender and age regarding the potential use of robots. An online survey was used to collect data, and the data was obtained from 407 participants. Contrary to the theory of anthropomorphism, but consistent with the Uncanny Valley and social comparison theories, the results of the study showed that the participants were adamant that it was not appropriate to use robots for 25 of the job positions out of 36. Humanoid robots were considered appropriate for positions that provide cleaning services, perform takeaway and delivery services, or where customers do not interact one-on-one during their stay. It was concluded that young people evaluated the use of robots in the sector more positively than older people. Similarly, women tended to make more positive evaluations than men. The original value of this research is based on the lack of studies evaluating the potential of using robots for positions in accommodation establishments.

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INTRODUCTION

The development of robotics, automation, and artificial intelligence (Tung & Au, 2018) means that robots have started to serve in many industrial fields, especially in automotive, electronics, metal, and chemical production, with increases in efficiency and cost reductions (Robotics Federation Annual Report, 2020). Robots are seen as the workforce of the future and have started to be used in accommodation businesses (Choi et al., 2020). One issue that needs to be understood is whether robots employed in the accommodation sector, which is seen as labor-intensive, will be accepted by hotel clients. This is because adapting any element to an area where production and consumption processes are carried out simultaneously is closely related to the acceptance of the people who consume the service.

Studies in different populations have examined the convenience and benefit provided by robots to hotel users (Ivanov et al., 2018a, 2018b; Lin & Mattila, 2021; Luo et al., 2021; Sharma et al., 2020; Tavitiyaman et al., 2022) and the attitudes of hotel managers towards service robots (Doğan & Vatan, 2019; Vatan & Doğan, 2021). The post-COVID-19 pandemic period, and the new climate where epidemics affect tourism movements may reveal the possible advantages and disadvantages of using robots compared to human workers in hotels (Kim et al., 2021; Wan et al., 2021; Wu et al., 2021; Zhang, 2021).

The labor-intensive nature of the accommodation sector meant it did not benefit much from the third industrial revolution, which introduced automation, or the fourth industrial revolution, which was identified with cyber-physical systems. Humanoid (anthropomorphic) robots, which are the result of the fifth industrial revolution, now allow human-robot collaboration and a high level of service customization and are thus an opportunity for accommodation businesses. The use of humanoid robots in hotels has a positive effect on attitude, customer satisfaction, and purchase intention (Jia et al., 2021).

Social relations directly affect service quality due to the intense human relations in the tourism sector and the high human-to-human interaction. It is thus important to examine the way users perceive robots in the tourism sector. This study examines the use of robots in accommodation businesses, which form a large part of the tourism sector, and the reaction of people to this situation. The human-ness of robots goes beyond appearance and is defined through human competencies, autonomy, and actions. Humanoid robots can have different personalities and communication styles (Murphy et al., 2017). Users prefer humanoid robots to other types of robots in hotels, and find them more empathetic (Christou et al., 2020a). Studies on human-robot interaction note that users may feel more empathy for service robots and treat them as one of their kind when they resemble humans (Huang et al., 2021).

Previous studies have evaluated the degree of similarity between robots and human beings, or whether they were convincingly humanoid. The originality of this study lies in asking potential users to evaluate humanoid robots according to different job positions in a hotel. The aim of the study is thus to gather evaluations from potential users, in this case hotel clients, regarding the use of robots in hotels, and whether this differs according to gender and age. The results will shed light on which positions robots can be used in the accommodation sector according to the acceptance of potential users.

The study consists of three parts. In the first part, the concepts related to the subject are explained and examples of applying the use of robots in accommodation establishments are given. A conceptual framework was created combining with anthropomorphism, Uncanny Valley Theory and Social Comparison Theory, and various studies in the literature on the use of robots in accommodation establishments. The study method and the findings of the study are then described. Finally, a comment and conclusion section consider theoretical and sectorial recommendations for the use of humanoid robots.

LITERATURE REVIEW

Conceptual Framework

The word robot originates in the Czech word "robota" which means "forced service" (Hockstein et al., 2007), which in turn is based on "rabu" which means "slave" in Old Slavonic (Online Etymology Dictionary, 2021). In the Merriam-Webster (2021) dictionary, robots are defined as machines with human-like features, capable of performing complex tasks and being directed through automatic control. The American Robotics Institute defines the concept of a robot as "material with a pre-programmed motion system to perform various tasks" (TUBITAK, 2021). According to these definitions, a robot can be conceptualized as a smart device that has learned how to achieve its aims thanks to pre-prepared codes.

The concept of a "robot" first appeared in the play RUR (Rossumovi Univerzální Roboti), written by Czech playwright Karel Capek in 1921, but the person who suggested the word was Josef Capek, not Karel (Kurfess, 2005). Although the word robot was used for the first time in 1921, the history of the first machines that could be called robots, in retrospect, goes back to before the Common Era, to the third millennium BCE. The ancient Chinese (Needham, 1991), Egyptian, and Greek (Rosheim, 1994) civilizations developed robot-like machines. Throughout classical antiquity, a strong connection was seen between the creation of "artificial beings" or automations using mechanics, and the divine. Some sculptures resembling gods and ideals of human beauty are equipped with complex mechanics (Fron & Korn, 2019).

The Golden Age of Islam (eighth to sixteenth century AD) witnessed the contributions of İsmail al-Jazari, who is known as the father of robotics, to the field of robotics. Leonardo Da Vinci, allegedly influenced by Al-Jazari, also contributed to developing the field of robotics, as well as being an iconic figure for the European Renaissance (Rusu & Rusu, 2020). The names Vaucanson and Von Kempelen come to the fore in the period between the post-Renaissance and the great technological leap in the 20th century (Geoghegan, 2020).

Electro was developed between 1937 and 1938 by the Westinghouse Electric Corporation, enabling today's modern humanoid robots to take shape, and was introduced at the New York Fair in 1939 (Qiu & Wang, 2020). In the early 1940s, Isaac Asimov and John Campbell proposed the idea of an intelligent robot that obeys and acts on human commands. Isaac Asimov is known for the following three laws regulating robot behavior in his compilation stories; a robot should not harm any human being, should obey people's orders as long as it is not harmed, and should protect its own existence (Hockstein et al., 2007: 114).

In 1961, a company named Unimation developed the first commercial robot, "Unimate", in the form of a robot arm (Engelberger, 1999). The robot was used by General Motors for jobs where human strength was not enough (Yıldız, 2018: 168). The robot industry has started to lead globally. The Waseda University WABOT project started in 1967, and produced the first humanoid robot, Wabot-1, which can communicate with humans and move objects (Ceccarelli et al., 2020). Dante II, which was developed in 1994, has become able to make expeditions for volcanic gas samples (Bares & Wettergreen, 1999).

Thanks to all these steps, robots gradually started to develop. Robots can now perform almost all humanoid physical actions. Researchers have tried to give robots the ability to understand human gestures, facial expressions, and even emotions. There are many types of robots, and it is possible to classify them in different ways according to their functional features, joint structures, control methods, working principles, and areas of use, and so on (Gürgöze & Türkoğlu, 2019). Accordingly, robots can be classified into two categories; industrial robots and mobile robots.

Industrial robots are used in assembly, cutting, and transportation jobs, because they can be programmed, controlled automatically and do work on their own. Mobile robots, on the other hand, are robots with high mobility, and are classified in six categories; multi-robots, swarm robots, micro-nano robots, bio-inspired robots, collaborative robots (cobots) and humanoid robots (Gürgöze & Türkoğlu, 2019). Robots which can think and behave like humans, make decisions, and respond to diverse situations, are known as humanoid robots. They were developed to perform various tasks undertaken by humans (Singh et al., 2018). Humanoid robots are built with the ability to connect and interact with humans and other robots, and to interpret information.

This study examines examples in the accommodation sector. The first examples of robotic applications being used in the tourism industry are the first electrically powered robot pool cleaner in 1967, which Hjalager (2015) described as among the first hundred innovations that changed tourism, and the first lawn mowers used in hotels, produced in 1989. As robot technology developed over time, robots began to be used by accommodation businesses in different departments. Although there are many different types of robots, those used in accommodation businesses are mobile social robots and are used as service robots. The goal of accommodation businesses is to serve guests (Tung & Law, 2017: 2500). There are thus many robot applications in accommodation businesses. Robots have many uses, and these uses can be classified as follows (Tuomi et al., 2021) to:

Support: Service robots may deal with routine tasks so that employees can spend their time in more sophisticated situations.

Substitute: Service robots may replace human employees entirely in some extent.

Differentiate: Service robots may be used as a tool to differentiate the service offered in order to attract new customers.

Upskill: The presence of service robots may mean that human employees require a new set of skills.

Improve: Service robots may improve efficiency in a way that allows businesses to allocate unused resources to improve their service offer.

Wirtz et al. (2018) drew a frame defining the differences between human and robot employees. They provided three levels (micro, meso, and macro), one of which focused on customer experience at the micro level. Service robots produce more homogenous output than human employees, such as in the customization and personalization of services, which can be delivered more consistently by robots, whereas human employees depend on their personal skill and effort. Robot employees also have no biases and are good at subordinate service roles. On the other hand, human employees have genuine emotions and the ability to solve problems in a creative way. The increase in human-robot interactions means that new robot technologies are also changing consumer experiences (Fusté-Forné & Jamal, 2021).

The Inter-Continental Hotel Group put Dash, a robot employee, into service at the Crown Plaza San Jose-Silicon Valley hotel in 2015. A robot named Savioke Relay can go up to the accommodation floors and bring guests the items they want. The Starwood Aloft Hotel appointed a robot steward named Boltr to provide comfort for hotel guests (İbiş, 2019). The task of the robot, named "Connie", developed by the Hilton Hotels Group in cooperation with IBM in 2016, is to help hotel guests by making theater and restaurant reservations, and arranging tours (Konstantinova, 2019). Guests can also ask the robot questions about food, beverages, and travel plans and get information about the hotel surroundings. Connie can understand many different languages and can respond to multiple guests simultaneously. As robots interact with guests, they learn new things and contribute to improving service quality (Zeng et al., 2020).

The Marriott Hotel operating in Belgium has a robot employee named "Mario". Mario can speak 19 different languages, hand over their room keys to guests and inform them about activities inside and outside the hotel. One of the first hotel trials without human personnel was started by a company called Alibaba in China (Alexieva, 2016). Robots perform operations in the reception department, such as check-in and check-out, and provide food service to guests. The robot in the bar of the hotel can prepare more than twenty kinds of cocktails and add the price to the consumer's invoice by scanning their face (Ohlan, 2018).

The ProPILOT Park Ryokan Hotel, on the other hand, is equipped with self-moving objects rather than humanoid robots (Kayıkçı & Bozkurt, 2018). A table waiting team of robots has been established in the bar section of the Royal Caribbean Hotel (Tung & Law, 2017). In the Henn-na Hotel in Japan, entry and exit procedures, room service and cleaning are all done by robots. Robots in the form of dinosaurs welcome the guests at the entrance of the Henn-na Hotel and help them find their rooms (Lukanova & Illieva, 2019). The hotel's robots can also communicate with guests in different languages and assist guests who want their luggage delivered to their room (İbiş, 2019). The Henn-na Hotel had a number of issues, however (Reis et al., 2020). It had to decommission almost half its robot employees since they were unable to perform the social tasks for which they were designed. Some hotel guests were understandably irritated by this. Many Henn-na hotel guests experienced disruptions due to language barriers that prevented them from communicating with robots. Another Henn-na passenger believed that the technology "did not yet exist" because in fact the robots were unable to assist clients when they needed it (Tung & Au, 2018). Henn-na therefore combined traditional human services with android receptionists, returning to a human-robot partnership (HRC).

As can be seen from the examples, robots are used in accommodation businesses to provide services in various departments or provide support for human personnel. Some are robotic receptionists, luggage carriers, room assistants, housekeeper robots and luggage storage robots. Some hotels employ robots to perform tasks that would otherwise require human intervention, such as delivering food and beverages to guest rooms and completing check-in and check-out processes. Developing robot technology is used in accommodation, travel, and catering businesses for reasons such as improving operational activities and making product quality consistent (Ivanov et al., 2017).

Theoretical Framework

The literature describes two conflicting basic theories that can be used to explain the production and use of humanoid robots. These theories are anthropomorphism and the Uncanny Valley. Social comparison theory is used to explain how to overcome the dissonance (contradiction) that arises where ideas, impulses, and attitudes are concerned. Anthropomorphism is the tendency of individuals to explain non-human objects as having human characteristics such as emotions or intentions (Epley et al., 2007). Anthropomorphism, in other words, is to attribute human-specific and human-like characteristics to objects or animals. This tendency, which has been common since ancient times, expresses a glorification of humans, and, in a way, although not fully, involves identifying with God (Pareyson, 1996).

"Why does man [sic] feel the need to humanize non-human beings?" Guthrie (1993) offers three reasons. The first is that people perceive what is happening in the environment through the information they have about it. The second reason is that people approach beings through humanization in order to eliminate the social emptiness they feel. The last reason is a need to build the world in a way that resembles humans (Khogeer, 2013: 29). These three reasons support the consideration of the concept of anthropomorphism (humanization) with semantic, social and cultural dimensions.

The main function of the semantic dimension is the point at which people predict and control the future behavior of other beings (Epley et al., 2007). The underlying causes of the social dimension involve the desire to control one's environment and to eliminate loneliness with the need to belong. The inadequacy in people's social relationships pushes them to perceive non-human beings as humanoid, thus removing the loneliness that the individual feels to some extent (Puzakova et al., 2009; Waytz et al., 2010). Culture is one of the most basic elements that affects the way people perceive their environment (Hofstede, 2011). An example of the culture dimension of anthropomorphism, in the context of consumption culture, is that the bear, which is a wild animal by nature, has become a favorite toy for babies (Delikan & Şener, 2020).

Prominent types of anthropomorphism seem to include visual anthropomorphism and linguistic anthropomorphism. Visual anthropomorphism involves identifying a product or brand with a certain human characteristic. Animation is a commonly used technique in visual anthropomorphism. However, there are situations when a real person can also represent an object; for instance, an overweight man appeared in a well-known car commercial for an airbag.

In linguistic anthropomorphism, human-specific qualities are transferred to an object or service through the words used. For example, in a coffee advertisement, coffee "gains its unique taste and smell" or "sweetens human relations" (Yücel Altınel, 2003). In addition to the visual and linguistic distinctions of anthropomorphism, there is also an idea that it can occur in four different ways (Di Salvo et al., 2005: 4-5):

• *Structural anthropomorphic form*: the imitation of human body structure and function. Shapes, mechanisms, or mechanisms that imitate human body features in their appearance or function, are examples of this type of anthropomorphism.

• *Gesture-based anthropomorphic form*: the use of movements and stances, which are elements of free behavior, to express a meaning or intention.

• *Character-based anthropomorphic form*: the reflection of human personality traits and social roles onto inanimate objects.

• *Awareness-based anthropomorphic form*: the principle of imitating human-specific features such as thinking and questioning. Robotics and artificial intelligence applications are examples.

The need for a more human world means that anthropomorphism is found in many different fields. Anthropomorphism is most frequently used in advertisements, toys, games and robots (Murphy et al., 2017). According to Baudrillard (1968: 169), one of the most common examples of anthropomorphizing objects is robots. Robots, which are a combination of full anthropomorphism and functionality, are the supreme object because of these features. Because people find humans more reliable than non-human objects, they gain control over objects and reduce uncertainty through anthropomorphism (Wang, 2017).

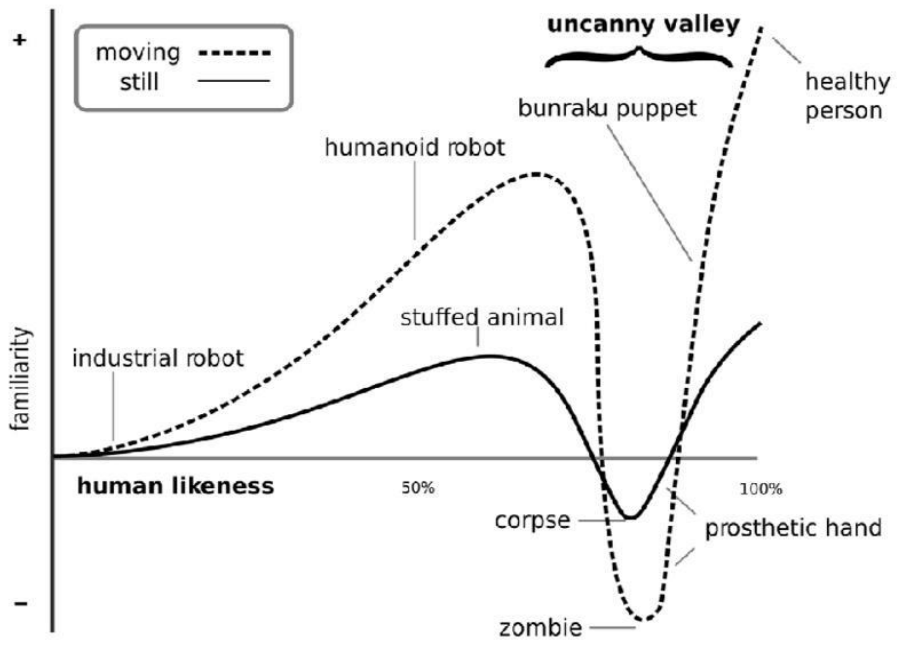

Figure 1. *Mori's Uncanny Valley Theory Graph* (*Hegel, 2016*)

According to MacInnis and Folkes (2017), there are three anthropomorphism strategies used in robot production. These are the uses of human-like features, such as a human face (a service robot with a human face, etc.), a human-like mind (a service robot with intentions, etc.), and a human personality (a friendly service robot, etc.). People thus try to make everything around them look like them, and they want to see a more human-like world. Sympathy for any object, person, or community, however, can be replaced by boredom, disgust, and hatred when it is exposed to that stimulus very often, for a long time, or when it evolves into something different from what was initially perceived by people. Doxey (1975) tried to explain this situation in terms of local people and tourists, in his Irritation Index. The Uncanny Valley Theory states that this arises in terms of robots due to their degree of resemblance to human beings.

Humanoid robots can imitate human behavior in many ways. Features such as the hands, eyes, speech skills, perception of the environment, and the ability to respond to people by interacting with them are attributed to robots from humans. People fill the world they live in with human-like creations, for reasons such as seeing them as more human and sometimes to feel less lonely (Puzakova et al., 2009; Waytz et al., 2010). The fact that the things they create have human-like characteristics makes them seem more sincere, friendly and safe. The Uncanny Valley theory by Japanese robot scientist Masahiro Mori can be confusing at this point. According to the Uncanny Valley theory, artificial designs and humanoid robots are attractive to humans up to a point (Brink et al., 2019), however, as the level of reality increases, negative emotions such as disgust, fear and hatred emerge, instead of positive ones (Geller, 2008: 11).

Figure 1 shows the levels of human similarity in artificial designs, and people's reactions to these similarities. According to Mori, if the appearance and behavior of a robot is humanoid, then a person's attitude towards the robot develops positively. However, as the robot begins to become more like a human, this attitude takes a negative turn. If humanoid features continue to be added to the robot, it can avoid being perceived as strange and frightening if humanoid features continue being added to the robot (Güngörmüş, 2018).

In Figure 1, the Uncanny Valley is depicted as a pit. The ideal location on the graph is the elevated section before falling into the valley, and after that point people start to feel hatred and disgust for an artificial object. This sense of the uncanny arises when humanoid robots are perceived as dangerous, in other words, when humans have no control over these robots.

If there is no threat, or it is at a very limited level, then robots are considered cute (Flach et al., 2012: 108). In this context, industrial robots are not perceived as uncanny because they do not have human-like features and are far from a real human in appearance. These robots are less likely to fall into the Uncanny Valley. Humanoid robots, on the other hand, raise expectations due to their human-like features. If its movements do not match a robot's humanoid appearance, it is perceived by people as uncanny and frightening (Tinwell et al., 2010).

At this point, the fact that the attitude of potential users towards robot employees can be affected by the general attitude emerges, because science is not rigid in its explanations, and there is variability in the ideas of the human species. How this general attitude has changed is not one of the subjects of this study, but it is a fact that change has taken place and further change is inevitable. One of the inferences of social comparison theory (Festinger, 1954), whose basic hypothesis is that people have an urge to evaluate their own ideas and competences, is that when there is incompatibility between ideas in a community, those ideas will change in order to eliminate the incompatibility. This can be interpreted as meaning that the minority will somehow accept the opinions of the majority after a certain point. On the other hand, another of the propositions in the same theory is that this comparison will be realized with the group that people see closest to them when comparing their ideas and competences. Humanoid robots in the hospitality industry can thus only be successful if the majority accept them. One of the main purposes of this study is to seek an answer to the question of how this level of acceptance is achieved in different job positions.

This study examined prominent and current research in the literature on the use of robots in accommodation establishments. Ivanov et al. (2017) revealed the difficulties faced by user companies if robots and service automation are used to serve tourists in hotels, restaurants, airports, event parks, travel agencies, museums and art galleries. Bowen and Morosan (2018) looked at how artificial intelligence and robotics are used in the hospitality industry, and offered ideas about how they might be used in 2030. Research indicates that robots will make up approximately one fourth of the workforce in the hospitality industry by 2030. Ivanov et al. (2018a) studied Russian adults and found that the use of robot personnel in accommodation enterprises was mostly supported by men. Ivanov et al. (2018b) studied Iranian tourists and found that they prefer human personnel in accommodation businesses, regardless of variables such as gender and age.

Choi et al. (2020) concluded that the services of human employees are perceived more positively in terms of interaction in the quality and physical service environment compared to the services provided by service robots. Doğan and Vatan (2019) discussed the opinions of hotel managers in Turkey about service robots in their study. They found that although hotel managers use technology intensively, they find the concept of a robot to be repulsive and emotionless, and most managers do not want to receive service from a service robot. Managers believe human communication is essential in the tourism industry. On the other hand, the managers thought that robots were advantageous in terms of not being late for work, not getting sick, not making mistakes, not asking for a raise, and working without limits. Yu and Ngan (2019) found that male and female participants from thirty-five different nationalities differed in their attitudes towards robot personnel.

According to Christou et al. (2020b), hotel guests have a positive attitude towards humanoid robots, however, when it comes to the danger that robots will take the jobs currently done by employees, their perceptions towards the robot change negatively. Xu et al. (2020) investigated how human resources experts believe the presence of service robots will affect leadership and human resource management in the hospitality industry. The results showed that while service robots are expected to increase the efficiency of hotel operations, they can create challenges such as higher costs, skill gaps, and significant changes to the organizational structure and culture of hotels.

Kuramoto et al. (2020) found that interacting with social robots was a pleasant experience for hotel guests, and many participants felt friendlier, livelier and less lonely due to this interaction. Sharma et al. (2020) revealed the attitudes of hotel guests towards robot staff in their study in India. According to their findings, hotel guests think that robots do not have social skills, and that they are unable to understand the special requests of the guests because they do programmed jobs. The participants stated that they were excited about the robot personnel, but that the balance between human and robot personnel should be adjusted. Yu (2020), on the other hand, found that human-like robots tend to provoke negative attitudes in potential users when there is any discussion, and that humans are more sensitive to robots with animated features. The study also found that many of the participants were nervous about the eyes of the robots.

Vatan and Doğan (2021), examined the attitudes of Turkish hotel employees towards robots. They found that the word robot evokes negative emotions in employees, and they believe that service robots may create problems when communicating with customers. Hotel workers also believe that service robots will lead to increased unemployment in the future. Fusté-Forné and Jamal (2021) discussed the opportunities and challenges of using service robots in the tourism industry in their study. Lin and Mattila (2021) revealed that the benefits of service robots and the appearance of the robot positively affect the attitude of hotel guests towards their adoption. They also found that with the increase in the benefits of robots, the attitudes of guests towards them changed in a positive way. Luo et al. (2021) analyzed the feelings of hotel guests towards robots in order to evaluate the service qualities of robots in hotels. They found that feelings towards robotic services were positively related to hotel service satisfaction, which plays an important role in determining the overall satisfaction of guests.

The studies examined in the literature reveal that robots used in accommodation businesses provide many benefits to businesses (Bowen & Morosan, 2018; Choi et al., 2019; Doğan & Vatan, 2019; Fusté-Forné & Jamal, 2021). On the other hand, people's attitudes towards humanoid robots differ. Some find humanoid robots friendly (Christou et al., 2020; Ivanov et al., 2018a; Kuramoto et al., 2020; Yu & Ngan, 2019), while others find them cold and frightening (Doğan & Vatan, 2019; Fusté-Forné & Jamal, 2021; Ivanov et al., 2017; Ivanov et al., 2018b; Lin & Mattila, 2021; Sharma et al., 2020; Yu, 2020; Vatan & Doğan, 2021; Yu & Ngan, 2019).

METHODOLOGY AND RESEARCH DESIGN

This study examines participant evaluations of the use of humanoid robots in job positions in accommodation businesses and presents ideas for academics interested in the subject and practitioners in the sector. Several studies examine attitudes towards the use of human robots in hospitality businesses (Christou et al., 2020a; Ivanov et al., 2018a, 2018b; Lin & Mattila, 2021; Sharma et al., 2020; Yu, 2020; Yu & Ngan, 2019), however, either the participants in these studies are a very specific group, or attitudes are measured on a departmental basis instead of for each position.

In this study, the participants’ evaluations of the use of humanoid robots for these positions were evaluated through a survey that was created after determining 36 job positions in accommodation enterprises. Forty-seven job positions were originally listed by first considering all departments in the accommodation establishments, and 36 job positions thought to be directly related to the sector were included in the scope of the research, in a 45-minute focus group study involving five tourism academicians and two sector managers. The main criterion for the positions on this list was that they were in an accommodation business of any size or were directly related to the accommodation industry. The job positions that did not meet this criterion were removed from the list.

The questionnaire created via Google Forms was shared on various social media sites, and non-random sampling methods were used in the collection of data. The results of the research thus cannot be generalized at the population level, but they can give an idea about the population. The entire data collection process took place online. Images of robots with and without humanoid forms were presented, and their features were explained, and then the participants were asked, “Do you think robots should be used in the following positions in the accommodation establishments? If you say it should be used, which robot, humanoid or non-humanoid, should be used for the position in question?” For each job position, they were asked to tick one of the options presented: “No, robots should not be used”, “Yes, humanoid robots can be used”, “Yes, non-humanoid robots can be used” and “Use a robot or not, I see no difference in either situation”.

In this study, the most important reason for determining the evaluations of demographically similar groups (gender and age) and testing whether there is a statistically significant difference between them is that this comparison will be made with the group they see closest to themselves when comparing the ideas and competences of people, which is one of the inferences of the Social Comparison Theory.

At the end of the data collection process, 407 people had been included. One of the advantages of online survey forms is that the form cannot be returned before it is completed, and so all surveys were included in the analysis. This met the required sample size in the 0.95 confidence interval for normally distributed series. In the findings section of the study, firstly, the frequency analysis tables for the demographic characteristics of the participants will be included in the findings section, and then the results of the chi-square test used in the analysis of the differentiation of a categorical variable in the independent groups are presented and interpreted.

RESULTS

The values for the demographic characteristics of the participants are shown in Table 1. Table 1 shows that when the age groups of the sample are evaluated, the groups other than the 65+ age group are very close to the demographic structure of the country. The CIA World Report (2020) shows that there is a great deal of overlap between the 25-54 age group and the 55-64 age group in age groups. There were deviations in the sample of the study, with the 18-24 age group being more common and the 65+ age group being relatively low. This is thought to be due to the data being collected using an online questionnaire.

Table 1. *Frequency Values for the Demographic Characteristics of the Participants*

Gender	**n**	**%**	**Monthly Income**	**n**	**%**
Female	215	52.8	Below minimum wage	103	25.3
Male	192	47.2	Minimum wage	104	25.6
Total	407	100	2826-5000	148	36.4
			5001-10000	38	9.3
Age	**n**	**%**	10000+	14	3.4
18-24	105	25.8	Total	407	100
25-34	122	30.0	**Education Level**	**n**	**%**
35-44	93	22.9	Primary school	69	17.0
45-54	37	9.1	High school	106	26.0
55-64	34	8.4	Associate/Bachelor's Degree	184	45.2
65+	16	3.9	Master’s/PhD	48	11.8
Total	407	100	Total	407	100

Not: Minimum wage on 14.12.2021: 2,826 TL; 1 Dollar: 14.38 TL.

Table 1 shows that when the age groups of the sample are evaluated, the groups other than the 65+ age group are very close to the demographic structure of the country. The CIA World Report (2020) shows that there is a great deal of overlap between the 25-54 age group and the 55-64 age group in age groups. There were deviations in the sample of the study, with the 18-24 age group being more common and the 65+ age group being relatively low. This is thought to be due to the data being collected using an online questionnaire.

While primary school graduates comprised 17.0% of the sample, half the individuals in the study were educated to the third level or had received any education within a university. There are approximately equal numbers of female (215) and male (192) participants. These rates reflect those of the country in general. Various analyses were conducted according to the gender and age of the participants, to determine whether gender affected ideas about whether robots should be used for each job position. In the next part of the study, extensive information is presented about the results of the analysis.

The study also gathered information about income levels, and the information obtained is presented in Table 1. Almost half the participants (50.9%) had a monthly minimum wage or less. This again shows that the sample is very close to the general demographic structure of the country, considering the minimum wage and unemployment rates in Turkey. As of October 2021, the unemployment rate in Turkey was 11.2%, and the number of people working at or below the minimum wage was 38.3% of all wage earners (TUIK, 2021). No analysis was carried out according to the education and income levels of the participants, these descriptive statistics simply present data about the study sample.

Table 2. *Descriptive Statistics for Participants' Reasons for Travel and Frequency of Accommodation*

Purpose of visit	**n**	**%**	**Frequency of stay**	**n**	**%**
Visit for friends and relatives	174	42.8	Never stayed in a hotel or etc.	98	24.1
Holiday	134	32.9	Less than once a year	172	42.3
Work Travel	30	7.4	Once a year	87	21.4
Health	12	2.9	Twice or three times a year	40	9.8
Others	57	14.0	Four times a year and more	10	2.5
Total	407	100	Total	407	100

Table 2 contains frequency data regarding the reasons for travel and the frequency of using accommodation establishments. Approximately one-third (32.9%) of the participants gave "holiday" as the reason for their last trip. It is striking that the most common reason for travel in this area is visiting friends and relatives (42.8%). However, 7.4% of the participants stated that they traveled for business reasons, and 2.9% stated that they traveled for health reasons.

Around a quarter (24.1%) of the respondents to the question about the frequency of use of accommodation establishments stated that they have never stayed in accommodation establishments, and those who stay less than once a year or once a year constitute 42.3% and 21.4% of the respondents, respectively. The regular customer base for the accommodation establishments is comprised of slightly more than 10% of the participants.

Table 3. *Statistics about Evaluations about the Use of Robots in Hospitality Businesses by Job Position*

Position	**Robots shouldn't be used**	**Humanoid robots can be used**	**Non-humanoid robots can be used**	**I see no difference in either situation**	**Gender**	**Age**
	n(%)	**n(%)**	**n(%)**	**n(%)**	**χ2 (p)**	**χ2 (p)**
P1-Waiter/Waitress	257 (63.14)	128 (31.45)	11 (2.70)	11 (2.70)	5.058 (.168)	**36.786 (.000)** [a]
P2-Barstaff	311 (76.41)	76 (18.67)	17 (4.18)	3 (0.74)	2.379 (.543)[a]	**34.443 (.000)** [a]
P3-Room Service Staff	85 (20.88)	232 (57.00)	35 (8.60)	55 (13.51)	4.703 (.195)	**58.438 (.000)** [a]
P4-Transfer Vehicle Driver	336 (82.56)	29 (7.13)	39 (9.58)	3 (0.74)	**9.325 (.017)** [a]	**43.023 (.000)** [a]
P5-Hotel Doctor	364 (89.43)	30 (7.37)	10 (2.46)	3 (0.74)	**11.538 (.005)** [a]	**17.385 (.000)** [a]
P6-Lifeguard	357 (87.71)	31 (7.62)	17 (4.18)	2 (0.49)	**10.533 (.007)** [a]	**24.480 (.019)** [a]
P7-SPA Attendant	342 (84.03)	52 (12.78)	11 (2.70)	2 (0.49)	**12.056 (.004)** [a]	**34.442 (.001)** [a]
P8-Masseur/ Masseuse	330 (81.08)	62 (15.23)	13 (3.19)	2 (0.49)	5.154 (.122) [a]	**43.319 (.000)** [a]
P9-Security	345 (84.77)	39 (9.58)	21 (5.16)	2 (0.49)	**10.187 (.010)** [a]	**30.905 (.002)** [a]
P10-Animator	325 (79.85)	59 (14.50)	17 (4.18)	6 (1.47)	6.511 (.081) [a]	**42.355 (.000)** [a]
P11-Common Area Cleaning Staff	27 (6.63)	196 (48.16)	122 (29.98)	62 (15.23)	3.539 (.316)	**39.977 (.000)** [a]
P12-Valet	339 (83.29)	41 (10.07)	22 (5.41)	5 (1.23)	**9.489 (.017)** [a]	**32.853 (.001)** [a]
P13-Cashier	239 (58.72)	131 (32.19)	29 (7.13)	8 (1.97)	5.375 (.140) [a]	**81.286 (.000)** [a]
P14-Concierge	333 (81.82)	49 (12.04)	16 (3.93)	9 (2.21)	**8.246 (.036)** [a]	**40.099 (.000)** [a]
P15-Bellhop	47 (11.55)	261 (64.13)	40 (9.83)	59 (14.50)	5.662 (.126) [a]	**52.017 (.000)** [a]
P16-Doorstaff	54 (13.27)	265 (65.11)	28 (6.88)	60 (14.74)	3.541 (.317)	**43.367 (.000)** [a]
P17-Night Manager	349 (85.75)	41 (10.07)	9 (2.21)	8 (1.97)	5.701 (.121) [a]	**29.453 (.002)** [a]
P18-PR Officer	351 (86.24)	37 (9.09)	11 (2.70)	8 (1.97)	6.145 (.092) [a]	**31.596 (.001)** [a]
P19-Receptionist	329 (80.84)	63 (15.48)	7 (1.72)	8 (1.97)	2.327 (.513) [a]	**47.553 (.000)** [a]

P20-Reservation Officer	315 (77.40)	66 (16.22)	16 (3.93)	10 (2.46)	3.879 (.275)	**44.457 (.000)** [a]
Position	**Robots shouldn't be used**	**Humanoid robots can be used**	**Non-humanoid robots can be used**	**I see no difference in either** situation	**Gender**	**Age**
	n (%)	**n (%)**	**n (%)**	**n (%)**	**χ2 (p)**	**χ2 (p)**
P21-General Manager	357 (87.71)	28 (6.88)	14 (3.44)	8 (1.97)	7.022 (.063) [a]	**24.264 (.018)** [a]
P22-HR Staff	352 (86.49)	36 (8.85)	13 (3.19)	6 (1.47)	6.690 (.078) [a]	**28.758 (.004)** [a]
P23-Finance Staff	283 (69.53)	59 (14.50)	32 (7.86)	33 (8.11)	7.630 (.050)	**36.861 (.000)** [a]
P24-Accounting Staff	279 (68.55)	60 (14.74)	34 (8.35)	34 (8.35)	7.095 (.069)	**39.535 (.000)** [a]
P25-Purchasing Staff	344 (84.52)	36 (8.85)	18 (4.42)	9 (2.21)	**8.269 (.038)** [a]	**31.311 (.002)** [a]
P26-Housekeeper	87 (21.38)	250 (61,43)	29 (7,13)	41 (10,07)	3.661 (.300)	**57.008 (.000)** [a]
P27-Marketing Staff	347 (85.26)	35 (8.60)	18 (4.42)	7 (1.72)	**12.881 (.004)** [a]	**31.158 (.002)** [a]
P28-IT Staff	332 (81.57)	41 (10.07)	25 (6.14)	9 (2.21)	**14.861 (.002)** [a]	**34.313 (.001)** [a]
P29-Event Planner	353 (86.73)	33 (8.11)	12 (2.95)	9 (2.21)	**10.199 (.016)** [a]	**28.009 (.005)** [a]
P30-Technician	318 (78.13)	47 (11.55)	28 (6.88)	14 (3.44)	**13.584 (.004)**	**42.138 (.000)** [a]
P31-Gardener	45 (11.06)	154 (37.84)	105 (25.80)	103 (25.31)	2.902 (.407)	**35.588 (.001)** [a]
P32-Warehouse Worker	36 (8.85)	165 (40.54)	100 (24.57)	106 (26.04)	4.105 (.250)	**39.417 (.000)** [a]
P33-Switchboard Operator	303 (74.45)	51 (12.53)	37 (9.09)	16 (3.93)	7.074 (.070)	**34.380 (.001)** [a]
P34-Laundry Staff	55 (13.51)	240 (58.97)	90 (22.11)	22 (5.41)	2.656 (.448)	**45.618 (.000)** [a]
P35-Kitchen Staff	298 (73.22)	6 (14.99)	38 (9.34)	10 (2.46)	**22.519 (.000)**	12.217 (.602) [a]
P36-Dishwasher Staff	50 (12.29)	246 (60.44)	88 (21.62)	23 (5.65)	6.236 (.101)	**43.252 (.000)** [a]
Average	257,6 (63.30)	95,3 (23.41)	32,5 (8.00)	21.5 (5,30)		

a. Fisher-Freeman-Halton Exact test.

Evaluating the average of the data in Table 3 shows that 63.30% of the participants believed robots should not be used in any position in an accommodation business. Those who approve of the use of humanoid robots comprised 23.41% of the total (63.78% of those who were not against the use of robots). Those who say humanoid robots should not be used made up 8.00% of the total (21.79% of those who are not against the use of robots) and form 5.30% of the total (14.44% among those who are not against the use of robots) who say that whether there is a robot or not will not make a difference.

There is a risk that this holistic perspective may lead to incorrect evaluations, however, because those who think that robots should not be used for 25 of the 36 positions that are the subject of the study number above the average. As can be seen in Figure 2, the rate for 17 positions (transfer vehicle driver, hotel doctor, lifeguard, general manager, event planner, human resources staff, public relations officer, night manager, marketing staff, security guard, purchasing staff, spa attendant, valet, receptionist, IT staff, masseur or masseuse, receptionist) was over 80%.

When this situation is interpreted, participants generally do not find the use of robots appropriate in positions that provide services related to people's health and bodies (hotel doctor, lifeguard, spa attendant, masseur or masseuse), in positions that concern life and property safety (security guard, valet, transfer vehicle driver), or in positions related to the management of the enterprise (general manager, HR staff, night manager, marketing staff, purchasing staff). Finally, it was concluded that the participants did not favor the use of robots for positions where they thought that one-to-one communication would be at a high level throughout the accommodation experience (event planner, public relations officer, concierge, and receptionist).

There are consistent results when we look at the other side of the coin, because it turns out that the participants will not be in one-to-one communication more or they do not see any harm in using robots for limited positions that have already been opened to automation. According to the results of the research, the positions where the "no robots should be used" option is below 20% were accepted as the areas where robots are accepted. These positions are also the positions where the use of humanoid robots is accepted; in other words, according to the participants, they are the positions with the highest value for the humanoid robot as a usable option. These are positions that provide cleaning services (housekeeping staff, laundry staff, dishwashing staff, common area cleaning staff), provide bring-and-take services (room service staff, bellboy, door staff), or positions where customers do not have one-to-one communication during the holiday experience (gardener, warehouse officer).

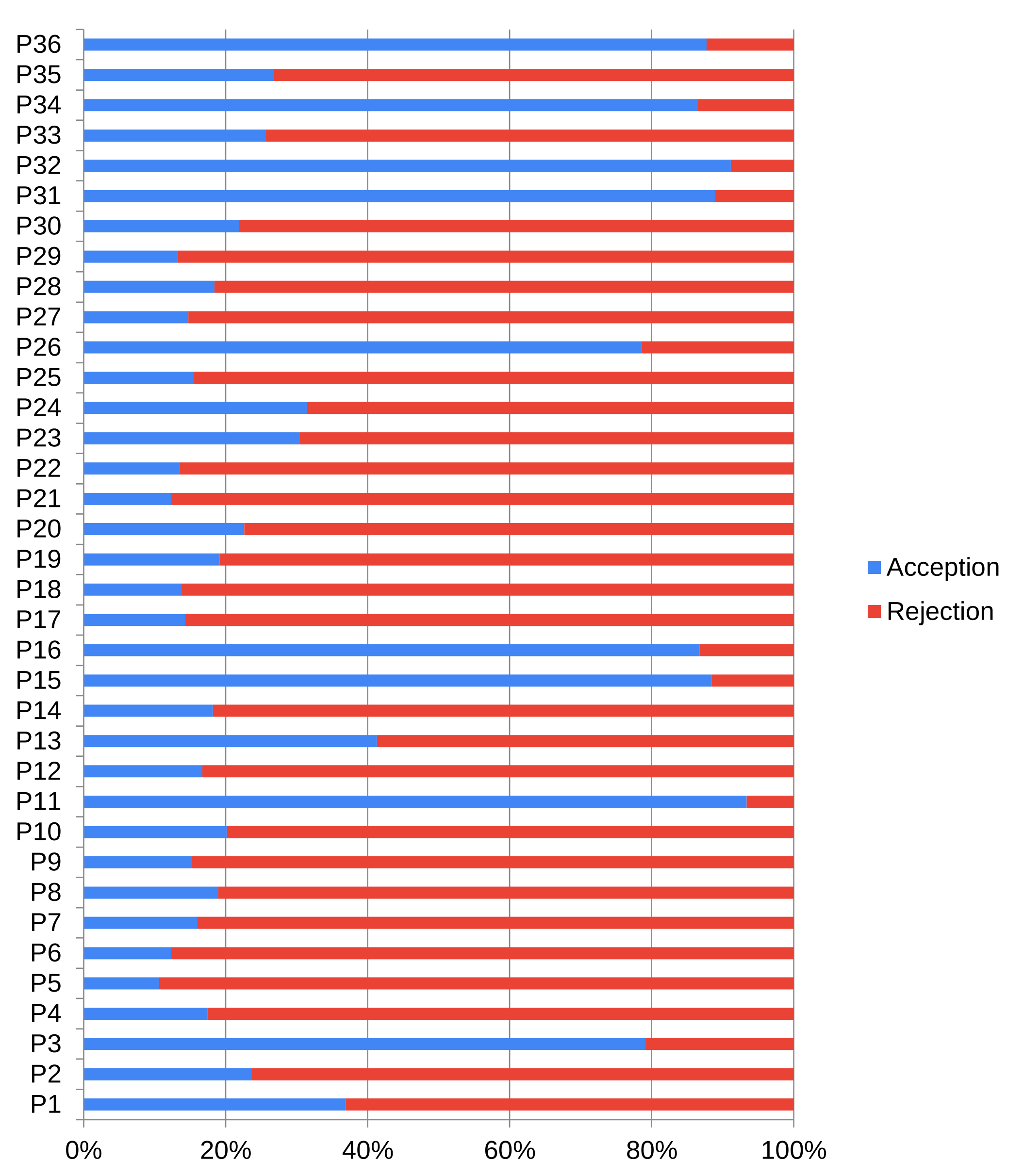

Figure 2. *Acceptance – Rejection Ratios for Robot Use Based on Job Positions*

Table 1 shows the chi-square results investigating the relationship between participant gender and their evaluations of robot use for the 36 positions considered within the scope of the research. The "a" icon in the table shows the Fisher-Freeman-Halton Test results used for RXC tables when the expected count less than 5 cells is more than 20% and the minimum expected count is less than 5, and a Monte Carlo simulation was used for the test. The Exact test p-value obtained with the Monte Carlo simulation (with 10,000 samples and 99% confidence interval) is the same as the Exact test p-value obtained with the Exact option, up to three zeros after the decimal point (Mehta & Patel, 2011).

Accordingly, the participants' evaluations of robot use by gender differ at a 0.05 level of significance for 13 positions (transfer vehicle driver, hotel doctor, lifeguard, spa attendant, security guard, valet, information officer, purchasing staff, marketing staff, IT staff, event planner, technician, and kitchen staff). Female participants were in favor of using robots for each of these 13 positions. It is significant that 11 of the 13 positions (except for technician and kitchen staff) that differ about the use of robots according to gender, are positions in which more than 80% of respondents recommended robots not be used.

A chi-square analysis was conducted to compare the ages of the participants and their evaluations of robot use. As can be seen in Table 3, there is a statistically significant difference in 35 (excluding kitchen staff) out of 36 positions in the accommodation sector. Evaluations that robots should not be used increase as age increases for 29 positions (excluding common area cleaning staff, bellhop, gardener, warehouse worker, dishwashing staff, and laundry staff). All 34 participants between the ages of 55-64 (for purchasing staff, marketing staff, and IT staff), all 16 participants aged 65 and over (for waiter/waitress, bartender, and finance staff), and 50 participants over 55 (for transfer vehicle driver, hotel doctor, lifeguard, spa attendant, masseur or masseuse, security guard, animator, valet, cashier, information desk officer, night manager, public relations officer, receptionist, reservation officer, general manager, human resources personnel, and event planning personnel) also expressed their opinions on not using robots is a summary of the age-technology acceptance relationship.

DISCUSSION AND CONCLUSIONS

Tourism is one of the industries in which artificial intelligence and robotic technologies are used in service automation. These technologies are integrated into business processes, especially the operations of accommodation businesses, to increase their productivity, offer consistent product quality and transfer a part of the service delivery process to customers (Ivanov et al., 2017). Developments in the field of robot technology mean that more and more independence opportunities are created for robots to make decisions. More humanoid features are being added related to perception, memory, dexterity and physical strength, and it is thus thought that robots will gain the capacity to reproduce human behaviors and will soon gain new human-like abilities by establishing various agreements with human or other robotic colleagues thanks to increased human-robot interactions (Arduengo & Sentis, 2019).

This is one of the first attempts to evaluate the potential use of robots, and beyond that, of humanoid robots, in the context of job positions in accommodation establishments among Turkish users. The participants strongly preferred not using any kind of robot for 25 of the 36 positions. These results are in line with previous findings from different cultures (Doğan & Vatan, 2019; Fusté-Forné & Jamal, 2021; Ivanov et al., 2018b; Lin & Mattila, 2021; Sharma et al., 2020; Yu, 2020; Vatan & Doğan, 2021). These are the positions that provide services for people's health and bodies, are related to the safety of life and property, and are related to the management of the business, and where the participants think that one-to-one communication will be at a high level throughout the accommodation experience.

Theoretical Implications

According to anthropomorphism theory, people tend to anthropomorphize everything, internalizing them by attributing unique traits. However, when it comes to robots, they evaluate their use strictly and negatively, because they find them unattractive, insincere and worry that they will take their place, and so on. The use of humanoid robots was found appropriate in nine positions: those that provide cleaning services, perform bring-and-go services, or where customers do not interact directly with them during the holiday experience. These results are also supported by the Uncanny Valley theory. The positions deemed suitable for the use of humanoid robots are those where guests interact less with the robots than in other positions. In summary, even if the guests find it appropriate to use humanoid robots in these areas, they do not want to stay together and communicate with them too much. It is reported in the literature that robots have been used by leading companies in the sector as waiters, room service staff, common area cleaning staff, bellhops, and gardeners (Alexieva, 2016; İbiş, 2019; Ivanov et al., 2017; Konstantinova, 2019; Lukanova & Illieva, 2019; Tung & Law, 2017; Zeng et al., 2020). In short, the findings are consistent with industry practices, and robots could thus be included in similar positions where robot use is appropriate.

The study also investigated whether there was a difference between attitudes to the use of robots in 36 job positions in accommodation businesses according to the gender and age of the participants, in the context of social comparison theory. It was observed that young people have a more positive attitude towards the use of robots than the elderly. The study also found that the participants differed according to gender in their attitudes towards whether a robot should be used or not. Male participants wanted robots to be used in fewer job positions, but female participants stated that they thought that robots could be used in more job positions.

It is particularly noteworthy that more female than male think more robotic staff should be employed in the kitchen staff and laundry staff positions. This finding is due to occupational gender stereotypes, and that this preference of women compared to men serves the occupational gender equality in question (Çilingir Ük et al., 2019). In other words, this preference stems from the fact that the job positions in question are perceived as socially feminine and they are deemed worthy of them, so women work more often in these positions than men, and that these jobs are roles that are stigmatized to women in their daily lives.

When the attitudes of the participants are evaluated according to their age, young participants were found more inclined to accept robot personnel, while participants over 50 were far from accepting robot personnel and prefer human personnel. This seems to be in line with the technology acceptance model, which aims to explain user attitudes towards the changing world of technology, their preferences for technology usage, and their possible resistance to using technology, and is frequently used in the field (Uğur & Turan, 2016: 103).

Managerial Implications

According to the findings of this study, there is a difference between attitudes according to age and gender. The younger participants began their lives in close contact with technology, whereas participants aged 50 and over began using technology at a later date, which may cause these people to be resistant to some forms of technology. Ivanov et al. (2018a) studied Iranian tourists and found that human personnel are preferred in accommodation businesses regardless of variables such as gender and age. Ivanov et al. (2018b) studied Russian adults and found that the use of robot personnel in accommodation enterprises was mostly supported by men. The degree of acceptance of robot personnel may thus vary among different nationalities. Similarly, Yu and Ngan (2019) found that male and female participants from different nationalities differ in their attitudes towards robot personnel.

In light of our research results, the managers of accommodation businesses targeting women, and especially young guests, could more easily adopt the use of robots in their establishments. In order to avoid negative results, however, as in the example of the Henn-na Hotel, this transformation should be implemented gradually by managers, rather than radically, to ensure the success of this digital transformation. The beginning of this transition should be the job positions in which the use of robots is more accepted in the study (common area cleaning, bellhop, doorstaff, gardener, warehouse worker, laundry staff, dishwasher staff). Similarly, managers should make the last transformation in 17 job positions where the use of robots is least accepted in the study, or not. As new generations who are more accepting of the digital transformation are added to the guest profile, we predict that acceptance rates for the use of robots in accommodation establishments will increase in the future.

Limitations and Future Research

Although the current study provides evidence of attitudes toward potential humanoid robot use in the hospitality industry, a number of limitations may have affected the results and seem worthy of discussion. First, a limited number of suitable samples were selected, but the findings are not representative of the entire population of Turkey, as probabilistic sampling methods were not used. Appropriate and larger samples could be used to ensure the generalizability of the findings in future studies. Second, changes in user attitudes towards robot use can be observed over time using longitudinal methods. Third, different positions can be added to the work carried out only in the positions determined in the accommodation enterprises in the future, and the subject can be applied to the positions in other tourism enterprises (travel, food and beverage enterprises, etc.). Fourth, while the role of culture in attitudes is known, a cross-cultural evaluation can compare the attitudes of users from different cultures regarding the use of humanoid robots in the industry. Fifth, the difference between demographics other than gender and age, and the effect of some accommodation indicators (frequency, reason, etc.) on attitudes can be examined. Sixth, the positions covered in the study could be considered in the context of the technology acceptance model developed by Ajzen and Feshbein (1975). Finally, this was a pilot study to identify potential robot use in 36 job positions in the hospitality industry, and a more in-depth analysis could be offered in the future by using a scenario-based approach to just a few positions.

Obviously, there is still much more work to be done in order to truly understand user evaluations of humanoid robot use; however, to our best knowledge, this is the first study to consider the evaluations of participants regarding the use of humanoid robots in accommodation establishments. We therefore hope that it serves as a preliminary study for broader research on the topic.

REFERENCES

Ajzen, I., & Fishbein, M. (1975). A Bayesian analysis of attribution processes. *Psychological Bulletin*, *82*(2), 261.

Alexieva, S. (2016). Sustainable tourism development between innovation competitiveness of the industry and effective communications in the digital era. *Journal of Science and Research, 9*, 41-50.

Arduengo, M., & Sentis, L. (2019). Robot economy: ready or not, here it comes. Retrieved April 25, 2021, from https://arxiv.org/abs/1812.01755.

Bares, J. E., & Wettergreen, D. S. (1999). Dante II: technical description, results, and lessons learned. *The International Journal of Robotics Research, 18*(7), 621-649.

Baudrillard, J. (1968). *Systeme des objets*. Paris, Gallimard: S.E.P.C. Press.

Bowen, J., & Morosan, C. (2018). Beware hospitality industry: robots are coming. *Worldwide Hospitality and Tourism Themes, 10*(6), 726-733.

Brink, K. A., Gray, K., & Wellman, H. M. (2019). Creepiness creeps in: uncanny valley feelings are acquired in childhood. *Child Development, 90*(4), 1202-1214.

Ceccarelli, M., Russo, M., & Morales-Cruz, C. (2020). Parallel architectures for humanoid robots. *Robotics*, *9*(4), 75.

Choi, Y., Choi, M., Oh, M., & Kim, S. (2020). Service robots in hotels: understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing and Management, 29*(6), 1-24.

Christou, P. A., Simillidou, A., & Stylianou, M. (2020a). Robots in tourism: tourists' perceptions over the use of anthropomorphic and other types of robots in services. *Apac CHRIE* 2020, October, Hong Kong.

Christou, P., Simillidou, A., & Stylianou, M. C. (2020b). Tourists' perceptions regarding the use of anthropomorphic robots in tourism and hospitality. *International Journal of Contemporary Hospitality Managemen, 32*(11), 3665-3683. http://dx.doi.org/10.1108/IJCHM-05-2020-0423.

CIA World Factboom. (2020). Retrieved November 13, 2021, from https://www.cia.gov/the-world-factbook/countries/turkey/#people-and-society.

Çilingir Ük, Z., Gültekin, Y., & Arslan, B. (2019). Turizm sektöründe mesleki toplumsal cinsiyet algılamalarının belirlenmesi: Üniversite öğrencileri üzerine bir uygulama. *Turizm Akademik Dergisi*, *6*(2), 75-97.

Delikan, B., & Şener, G. (2020). Marka maskotlarındaantropomorfizm kullanımına yönelik göstergebilimselbir analiz: Arçelik markası robot çelik vakası. *Manas Sosyal Araştırmalar Dergisi, 9*(3), 1836-1854.

Di Salvo, C., Gemperle, F., & Forlizzi, J. (2005). Imitating the human form: four kinds of anthropomorphic form. Retrieved April 19, 2021, from http://www.cs.cmu.edu/~kiesler/anthropomorphism-org/pdf/Imitating.pdf.

Doğan, S., & Vatan, A. (2019). Hotel managers' thoughts towards new technologies and service robots at hotels: a qualitative study in Turkey. In: C. Cobanoglu, M. Cavusoglu, A. Corbaci (eds.) *Advances in Global Business and Economics*, Vol. 2, ANAHEI Publishing, Sarasota, 382-399.

Doxey, G. V. (1975). A causation theory of visitor resident irritants: methodology and research inferences. Paper Presented at the *Travel and Tourism Research Association Sixth Annual Conference Proceedings*, San Diego, 195-198.
Engelberger, J. F. (1999). Historical perspective and role in automation. Handbooks of industrial robotics. In S. Y. Nof (eds.), *Handbook of industrial robotics*, New York, NY: John Wiley & Sons, 3-10.
Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: a three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864-886.
Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, *7*(2), 117-140.
Flach, L. M., Moura, R. H., Musse, S. R., Dill, V., Pinho, M. S., & Lykawka, C. (2012). Evaluation of the uncanny valley in CG characters, in *Proceedings of the Brazilian Symposium on Computer Games and Digital Entertainment* (SB Games) (Brasìlia), 108-116.
Fron, C., & Korn, O. (2019). A short history of the perception of robots and automata from antiquity to modern times. *In Social Robots: Technological, Societal and Ethical Aspects of Human-Robot Interaction*, Offenburg, Germany: Springer, Cham.
Fusté-Forné, F., & Jamal, T. (2021). Co-creating new directions for service robots in hospitality and tourism. *Tourism and Hospitality, 2*(1), 43-61.
Geller, T. (2008). Overcoming the uncanny valley. *IEEE Computer Graphics and Applications*, *28*(4), 11-17.
Geoghegan, B. D. (2020). Orientalism and informatics: alterity from the chess-playing Turk to Amazon's mechanical Turk. *Ex-position*, *43*, 45-90.
Guthrie, S. E. (1993). *Faces in the clouds: a new theory of religion*. New York, Oxford: Oxford University Press.
Güngörmüş E. (2018). İnsanın karanlığı ve Freud. Retrieved May 5, 2021, from http://www.ercankesal.com/makaleler-sunumlar/insanin-karanligi-ve-freud/.
Gürgöze, G., & Türkoğlu, İ. (2019). Kullanım alanlarına göre robot sistemlerinin sınıflandırılması. *Fırat Üniversitesi Mühendislik Bilimleri Dergisi*, *31*(1), 53-66.
Hjalager, A. M. (2015). Turizmi değiştiren 100 yenilik (Çeviren: Güler, O., Akdağ, G., Çakıcı, A. C. ve Benli, S.). *Anatolia: Turizm Araştırmaları Dergisi, 26*(2): 290-317.
Hockstein, N., Gourin, C., Faust, R., & Terris, D. (2007). A history of robots: from science fiction to surgical robotics. *Journal of Robotic Surgery*, *1*, 113-118.
Hofstede, G. (2011). Dimensionalizing cultures: the Hofstede model in context. *Online Readings in Psychology and Culture, 2*(1), 1-26.
Huang, H. L., Cheng, L. K., Sun, P. C., & Chou, S. J. (2021). The effects of perceived identity threat and realistic threat on the negative attitudes and use intentions toward hotel service robots: the moderating effect of the robot's anthropomorphism. *International Journal of Social Robotics, 13*, 1599-1611.
Ivanov, S. H., Webster, C., & Berezina, K. (2017). Adoption of robots and service automation by tourism and hospitality companies. *Revista Turismo & Desenvolvimento, 27*(28), 1501-1517.
Ivanov, S., Webster, C., & Garenko, A. (2018a). Young Russian adults' attitudes towards the potential use of robots in hotels. *Technology in Society, 55*, 24-32.
Ivanov, S., Webster, C., & Seyyedi, P. (2018b). Consumers' attitudes towards the introduction of robots in accommodation establishments. *Tourism: An International Interdisciplinary Journal, 66*(3), 302-317.
İbiş, S. (2019). Turizm endüstrisinde robotlaşma. *Türk Turizm Araştırmaları Dergisi*, *3*(3), 403-420.
Jia, J. W., Chung, N., & Hwang, J. (2021). Assessing the hotel service robot interaction on tourists' behaviour: the role of anthropomorphism. *Industrial Management & Data Systems. 121*(6), 1457-1478.
Kayıkçı, M. Y., & Bozkurt, A. K. (2018). Dijital çağ vealphakuşağı, yapay zeka uygulamaları ve turizme yansımaları. *Sosyal Bilimler Metinleri, 1*, 54-64.
Khogeer, Y. K. (2013). *Brand anthropomorphism: the literary lives of marketing mascots* (PhD Thesis). University of Liverpool, Management School, Liverpool.
Kim, S. S., Kim, J., Badu-Baiden, F., Giroux, M., & Choi, Y. (2021). Preference for robot service or human service in hotels? Impacts of the covid-19 pandemic. *International Journal of Hospitality Management, 93*, 2-12.

Konstantinova, S. (2019). Digital transformation in tourism. *Knowledge International Journal, 35*(1), 188-193.

Kurfess, Thomas R. (2005). *Robotics and automation handbook.* Abingdon: Taylor and Francis.

Kuramoto, S., Sawada, H., & Hartono, P. (2020). Visualization of topographical internal representation of learning robots. *In 2020 International Joint Conference on Neural Networks (IJCNN)*, 1-7.

Lin, I., & Mattila, A. (2021). The value of service robots from the hotel guest's perspective: a mixed-method approach. *International Journal of Hospitality Management*, *94*, 2-4.

Lukanova, G., & Ilieva, G. (2019). Robots, artificial intelligence and service automation in hotels. In S. Ivanov and C. Webster (eds.), *Robots, artificial intelligence, and service automation in travel, tourism, and hospitality*. Bingley: Emerald Publishing, 157-183.

Luo, J. M., Vu, H. Q., Li, G., & Law, R. (2021). Understanding service attributes of robot hotels: a sentiment analysis of customer online reviews. *International Journal of Hospitality Management, 98*(103032), 1-10.

MacInnis, D. J., & Folkes, V. S. (2017). Humanizing brands: when brands seem to be like me, part of me, and in a relationship with me. *Journal of Consumer Psychology*, *27*(3), 355-374.

Mehta, C. R., & Patel, N. R. (2011). *IBM SPSS exact tests*. Armonk, NY: IBM Corporation.

Merriam-Webster English Dictionary (2021). *Robot*. Retrieved May 11, 2021, from https://www.merriam-webster.com/dictionary/robot.

Murphy, J., Gretzel, U., & Hofacker, C. (2017). Service robots in hospitality and tourism: investigating anthropomorphism. *In 15th APacCHRIE conference* (Vol. 31), Retrieved May 11, 2021, from http://heli.edu.au/wp-content/uploads/2017/06/APacCHRIE2017_Service-Robots_paper-200.pdf

Needham, J. (1991). *Science and civilisation in China*. *History of scientific thought*. Cambridge: Cambridge University Press.

Ohlan, R. (2018). Role of information technology in hotel industry. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *3*(2): 277-281.

Online Etymology Dictionary (2021). Retrieved September 22, 2021, from https://www.etymonline.com/word/robot.

Pareyson, L. (1996). *Ontologie de la liberte*, Retrieved from www.lyber-eclat.net/lyber/pareyson/ontoll-12.html.

Puzakova, M., Kwak, H., & Rocereto, J. (2009). Pushing the envelope of brand and personality: antecedents and moderators of anthropomorphized brands. *Advances in Consumer Research, 36*, 412-420.

Qiu, Z., & Wang, Z. (2020). Technology forecasting based on semantic and citation analysis of patents: a case of robotics domain. Big Data and Smart Computing (BigComp) 2021 *IEEE International Conference*, 203-209.

Reis, J., Melão, N., Salvadorinho, J., Soares, B., & Rosete, A. (2020). Service robots in the hospitality industry: The case of Henn-na hotel, Japan. *Technology in Society*, *63*, 101423.

Robotics Federation Annual Report (2020). Retrieved November 16, 2021, from https://ifr.org/img/worldrobotics/Executive_Summary_WR_2020_Industrial_Robots_1.pdf.

Rosheim, M. E. (1994). *Robot evolution: The development of anthrobotics.* New York: John Wiley & Sons.

Rusu, N., & Rusu, A. (2020). Filosofiainvențiilor Lui Leonardo Da Vinci siimportanțalorînevoluțiamecanicii. *In Conferințatehnico-ştiinţifică a studenţilor, masteranzilorşidoctoranzilor,* 503-506.

Sharma, R., Uniyal, M., & Sharma, N. (2020). Guest attitude towards introducing automation using service robots in hotels of Delhi. *International Journal of Advanced Science and Technology*, *29*(5), 2930-2937.

Singh, H., Unger, J., Zariffa, J., Pakosh, M., Jaglal, S., Craven, B. C., & Musselman, K. E. (2018). Robot-assisted upper extremity rehabilitation for cervical spinal cord injuries: a systematic scoping review. *Disability and Rehabilitation: Assistive Technology*, *13*(7), 704-715.

Tavitiyaman, P., Zhang, X., & Tsang, W. Y. (2022). How tourists perceive the usefulness of technology adoption in hotels: Interaction effect of past experience and education level. *Journal of China Tourism Research, 18*(1), 64-87.

Tinwell, A., Grimshaw, M., & Williams, A. (2010). Uncanny behavior in survival horror games. *Journal of Gaming & Virtual Worlds, 2*(1), 3-25.

TUBITAK (2021). *Robot*. Retrieved May 28, 2021, from http://www.bilimteknik.tubitak.gov.tr/sites/default/files/bilgipaket/robotik/tanimlar.html.

TUIK (2021). İşsizlik oranları. Retrieved December 17, 2021, from https://www.tuik.gov.tr/.

Tung, V. W. S., & Au, N. (2018). Exploring customer experiences with robotics in hospitality. *International Journal of Contemporary Hospitality Management, 30*, 2680-2697.

Tung, V. W. S., & Law, R. (2017). The potential for tourism and hospitality experience research inhuman-robot interactions. *International Journal of Contemporary Hospitality Management, 29*(10), 2498-2513.

Tuomi, A., Tussyadiah, I. P., & Stienmetz, J. (2021). Applications and implications of service robots in hospitality. *Cornell Hospitality Quarterly*, *62*(2), 232-247.

Uğur, N. G., & Turan, A. H. (2016). Mobil uygulama kabul modeli: birölçek geliştirme çalışması. *Hacettepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 34*(4), 97-126.

Vatan, A., & Dogan, S. (2021). What do hotel employees think about service robots? A qualitative study in Turkey. *Tourism Management Perspectives, 37*, 100775.

Wan, L. C., Chan, E. K., & Luo, X. (2021). Robots come to rescue: how to reduce perceived risk of infectiousdiseaseincovid19-strickenconsumers? *Annals of Tourism Research, 88,* 103069.

Wang, W. (2017). Smartphones as social actors? Social dispositional factors in assessing anthropomorphism. *Computers in Human Behavior, 68*, 334-344.

Waytz, A., Epley, N., & Cacioppo, J. T. (2010). Social cognition unbound: insights into anthropomorphism and dehumanization. *Current Directions in Psychological Science, 19*(1), 58-62.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, *29*(5), 907-931.

Wu, J., Zhang, X., Zhu, Y., & Yu-Buck, G. F. (2021). Get close to the robot: the effect of risk perception of covid-19 pandemic on customer–robot engagement. *International Journal of Environmental Research and Public Health, 18*(12), 6314.

Xu, S., Stienmetz, J., & Ashton, M. (2020). How will service robots redefine leadership in hotel management? Adelphi approach. *International Journal of Contemporary Hospitality Management, 32*(6), 2217-2237.

Yıldız, S. (2018). Turist rehberliği mesleğinde robot rehberlerin yükselişi. *Süleyman Demirel Üniversitesi Vizyoner Dergisi, 10*(23), 164-177.

Yu, C. E. (2020). Humanlike robots as employees in the hotel industry: thematic content analysis of online reviews. *Journal of Hospitality Marketing and Management*, *29*(1), 22-38.

Yu, C. E., & Ngan, H. F. B. (2019). The power of head tilts: gender and cultural differences of perceived human vs human-like robot smile in service. *Tourism Review*, *74*(3), 428-442.

Yücel Altunel, H. (2003). Reklamlarda insanbiçimsellik. *İletişim Araştırmaları, 1*(1), 107-121.

Zeng, Z., Chen, P. J., & Lew, A. A. (2020). From high-touch to high-tech: covid-19 drives robotics adoption. *Tourism Geographies, 22*(3), 724-734.

Zhang, Y. (2021). A big-data analysis of public perceptions of service robots amid covid-19. *Advances in Hospitality and Tourism Research (AHTR), 9*(1), 234-242.

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