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Shared experience in pretrip and experience sharing in posttrip: A survey of Airbnb users

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ABSTRACT

This research focuses on travelers' use of shared experiences during their pretrip decision-making and their posttrip behavior in sharing their experiences. On the basis of information processing and literature on experience sharing, we developed hypotheses on how travelers make their purchase decisions on a smart tourism platform, adopting the experiences shared by others (pretrip), and how the quality of their travel experience and perceived information discrepancy affected their behavior in sharing their experience (posttrip). By testing these hypotheses using survey data from 411 Korean users of Airbnb, we draw conclusions on how firms should manage the flow of travelers' experience information and design smart tourism platforms.

1. Introduction

With the development of information and communication technologies (ICTs), various tour-related services have emerged and proliferated, especially in the hospitality industry. These services include Airbnb, Yelp, Orbitz, and TripAdvisor. The growth of these businesses changed the way tourists plan their travel, search for information, and share their experiences [1,2]. Smart tourism has a direct effect on tourists' experiences through access to detailed information and the introduction of social platforms that permit them to interact with each other. Thus, smart tourism develops a "new social system" [3] in which users share information, read reviews on tourist attractions and hotels, and participate in interactive travel forums [4].

A theoretical framework is necessary to explain more constructively the process of tourists' decision-making during their trip planning and their decisions to share their experiences afterward, both of which are a part of a smart tourism ecosystem (STE). A number of researchers have examined the demographics, motivations, and new media involved in travelers' use of travel websites [5–7]. However, in the context of smart tourism, most investigators have focused on case studies [8,7]. Thus, there is a need to empirically explore in a smart tourism platform how travelers adopt others' experiences and what factors influence their decisions to share their own experiences later.

This research focuses on travelers' use of shared experiences during their pretrip decision-making and their posttrip behavior in sharing their experiences. By integrating literature on experience sharing from marketing and service operations research and using information-processing theory as an overarching framework, we develop a theoretical framework on how a smart tourism platform and travelers interact over the course of their experience as tourists. Our findings make managerial contributions by suggesting how in the pretrip phase tourists use information uploaded by others to form their expectations and make their purchasing decisions in anticipation of their travel and destinations. Moreover, determining how travelers evaluate their experience during a trip and decide to share their experiences afterward enhances our understanding of how firms should design their interactive platform in smart tourism. On the basis of our results, we suggest design implications for smart tourism platforms toward the end of this paper.

The following were the research questions for this study: What factors influence traveler's adoption of shared experiences in smart tourism and determine their purchase intentions? How do discrepancies between expectations and actual experience

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influence proactive sharing of experiences? Our research is composed of two parts. The first part focuses on the anticipatory phase of travel and examines how social distance and breadth of review affects the decision-making of tourists using a smart tourism platform. The second part concerns a reflective phase in which travelers recall and assess their travel experiences and decide whether to share them. Users of smart tourism platforms search for information, make purchasing decisions about tours, experience the tours, and decide whether to share their experiences. This stream of activities can be explained by information-processing theory, namely that users constantly seek experience information to reduce the uncertainties of trips and make decisions about sharing their experience information to inform others who are engaged in making similar decisions [9].

This research uses 411 users of Airbnb in South Korea to explore travelers' experience of the information flow on a smart tourism platform. We conducted an experiment to test the first model by focusing on the effects of social distance and review breadth on purchase decisions. Six experimental conditions were developed as scenarios following a 3×2 factorial design to explore the effect of social distance and review breadth. A survey was used to examine the second model by asking respondents to reflect on their recent travel experiences; their responses were used to investigate their propensities to share their experiences.

The paper is organized as follows: first, we review the theoretical and empirical literature on the sharing of experiences in smart tourism and the flow of experience information in terms of tourists' experiences. In the next section, we develop hypotheses based on this review of the relevant literature. We then describe the research context and introduce our data set and analytical methods. The results of the study come next, along with a discussion of our findings and their implication. We conclude the paper with discussions of the contributions of our research, its limitations, and our suggestions for future research.

2. Theoretical framework

2.1. Smart tourism platform using an information-processing perspective

Information-processing theory mainly describes how people solve problems [10,11]. On a smart tourism platform, tourists are the main problem solvers who attempt to seek optimal trip solutions such as reasonably priced hotels and restaurants. To gather the information necessary for their decisions, users refer to other people's feedback comments on tourism platforms. However, because of the multiplicity of random experiences on tourism platforms, users cannot easily find the information relevant to their needs. This is because of the uncertainty and equivocality they encounter [9]. Uncertainty means a lack of information that is both relevant and important to the solution of their problem [12]. Thus, uncertainty decreases when more information is available. Equivocality represents ambiguity. In other words, when there is conflicting information, users become confused about which information to trust [13,14]. Equivocality decreases when decision makers can discern which information to trust and adopt. If tourism platforms were designed to reduce these two factors, uncertainty and equivocality, then they could help users make better decisions about their trips.

When users are highly uncertain about where to stay or what to eat during a trip, the requirements for information processing increase accordingly [15]. Previous studies explore the mechanisms for reducing discrepancies between information requirements and information capacities [16,17]. In the specific context of tourism, recent studies such as by Ho et al. [18] suggested a conceptual framework of Web users' tourism information. In this framework, users constantly search for information to aid their decision-making. Papathanassis and Knolle [19] also suggested that users utilize various sources of information including reviews of the users in tour-related decision-making. Boyd and Bahn [20], on the basis of the information-processing perspective, also regard the users as information-searching entity to achieve decision-making certainty and cognitive simulation. In brief, they suggest two ways to reduce the imbalance. One is by providing guidelines. The other is by increasing the role of a central actor (manager). This central actor would assist decision-making by reducing overlapping decision points and clarifying the origin of information. Similarly, a close social distance between an information provider and a recipient (problem solver) would reduce equivocality because a problem solver then considers the information as trustworthy in assisting the decision-making process. Moreover, just as the guidelines do, breadth of information decreases uncertainty by reducing the need to communicate.

However, the extant literature in information-processing theory largely focuses on the mechanism to enhance information-processing capability and decision-making performance within the organization. Tushman and Nadler [21] regard organizations as information-processing systems and suggest that task characteristics would affect the organizational design. Daft and Lengel [10] also focus on managerial behavior in managing the information-processing procedure to reduce uncertainty. Although Song et al. (2005) [22] explore the role of lead user and supplier networks as the mechanisms for increasing the capacity for information processing, their role remains supplementary. In this research, we attempt to use information-processing theory to show how users—who typically reside outside the organization—and smart tourism platforms (organization) can interact in a way that increases users' information-processing capabilities. We also suggest how smart tourism platforms can facilitate users' decision-making by decreasing uncertainty and equivocality through proper interactive design of the platform.

In addition, users decide whether to share their travel experiences on smart tourism platforms to reduce others' uncertainty and equivocality. From the perspective of information-processing theory, users' behavior in sharing their experiences works as an important mechanism to facilitate information processing in a STE (Smart Tourism Ecosystem). Thus, we explore what factors in a smart tourism platform would increase their sharing propensities. This effort contributes to the extant literature of information processing by suggesting iterative processes to enhance the problem-solving capabilities of users on a smart tourism platform.

2.2. Smart tourism and electronic word-of-mouth

Electronic word-of-mouth (eWOM) has grown with the development of new media channels and Web 2.0 tools such as consumer review sites and social network platforms in which customers share their experiences and exchange product information [23]. The extant literature on investigations into the effect of eWOM can be classified into two streams: market-level analysis and individual-level analysis. Market-level analysis focuses on parameters such as product sales, whereas individual-level analysis regards the eWOM effect as a personal influence [24]. Our research deals with both levels of analysis by inspecting how shared experiences influence adoption by an individual actor and how tourists form their purchase intentions after travel. Cheung and Thadani [24] also introduced an integrative framework, based on a stimuli-response framework, of the impact of eWOM communication. According to their research, argument quality, valence, sidedness, and volume work as stimuli to form responses leading to adoption and purchase of a product. In the tourism context, Ladhari and Michaud [25] contend that comments on the Facebook network influence hotel reservation intentions, attitudes, trust, and perceived quality of the hotel website. Lee et al. [26] suggest that strong identification strengthens customers' sharing intentions in online travel communities. However, the research on the effect of eWOM is fragmented, and an integrated framework is necessary to explain how the flow of experience information and tourists' decision-making interact with each other.

In a smart tourism context, we also attempt to integrate the prior findings of the effect of eWOM within the framework of information-processing theory. Prior studies in eWOM have theoretical backgrounds on the interpersonal theory [27–29], attribution theory [30,31], cognitive fit theory [32], impression formation [33], social ties [34], and source credibility literature [31,35]. By introducing information-processing arguments, we contribute to the richness of the theoretical foundations of eWOM studies. In addition, we introduce the impact of social distance and breadth of shared experience as factors leading to the adoption of shared experience. As smart tourism forms a new social system based on the development of information and communication technologies [3], the social distance based on the social service network (SNS) should be taken into account. In particular, we considered not only direct connections but also indirect connections on the basis of mutual friends to discern the magnitude of the impact of social distance.

2.3. Tourists' experience sharing in smart tourism

Smart tourism evolved from e-tourism and has been recently studied because of the rise of technologies based on sensors, big data, open data, and information exchanges [36]. In smart tourism, technology enables people to freely access a huge set of data and share their experiences, thus changing the way people interact with each other [37]. For instance, Yelp, Airbnb, Orbitz, and TripAdvisor have platforms that allow travelers to search for others' specific travel and destination experiences and allow these same prospective travelers to later share their own experiences. Moreover, most of these platforms integrate travelers' social network data based on a social network service (e.g., Facebook) to deliver personalized recommendations.

Users' participation in sharing travel experiences is a core component within the STE [38] in which user–user interaction is at the forefront in accelerating the sharing of tourism experiences [37]. Thus, the STE capitalizes on extensive and intensive information sharing and co-creation of values by tourism consumers [39]. We suggest "experience sharing" as a core value in the context of smart tourism because travelers are important sources of information and also users who take advantage of the information that promotes the development of the STE. In the marketing and service operations literature, customers' shared experiences are viewed as a value creation through cocreation [40,41]. That is, customers receive value through personalized experience by engagement and involvement in the process of consuming services [42].

From the perspective of sharing experiences of tours, Xiang and Gretzel [43] determined that social media is a major information source during the pretrip phase. To expand this research, it is important to explore how information about actual experiences affects tourists' decisions about various elements of their travel and choice of destinations. With the development of services such as Airbnb, travelers have access to a huge amount of information that not only is shared by their closest friends but also originated from strangers. Thus, it is necessary to figure out how in the pretrip phase tourists use information uploaded by others to form expectations for their travel. Moreover, learning how travelers arrive at their evaluations of their travel experience during their trip and reach their decisions on whether to share their experiences later would enhance our understanding of the way firms should design their interactive platforms in smart tourism.

2.4. The flow of information in tourists' experiences

The tourist experience is composed of three phases: anticipatory, experiential, and reflective [6]. According to these three phases, tourists manage their planning, search for information, and make decisions [44]. In the anticipatory phase, tourists recall their previous travel experience and assess their projected travel within this context. The search for travel information begins in this phase and continues throughout their travel. In the experiential phase, tourists implement their plans and adjust them to the circumstances they encounter. During this process, tourists purchase travel products such as hotel, flight, and restaurant reservations

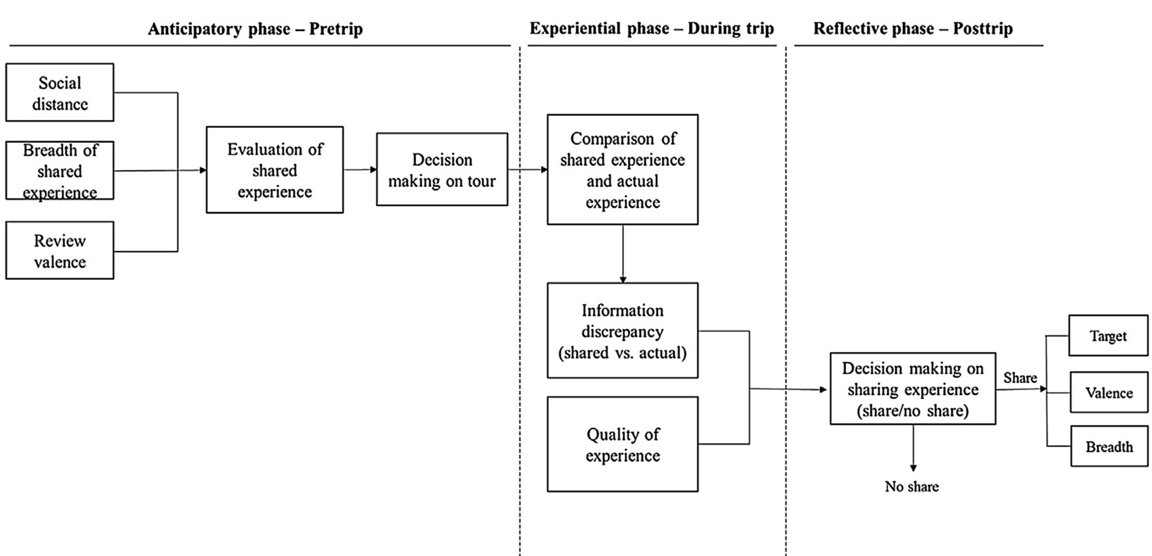

Fig. 1. The flow of experience information and travelers' decision-making.

and execute their travel plan. Finally, in the reflective phase, tourists evaluate their completed trip and lessons they learned in the anticipation of their next trip.

In smart tourism, tourism services should be designed to accommodate tourists in the sequence suggested above. Gretzel et al. [36] discussed the role of firms in enhancing tourists' satisfaction in terms of smart tourism. Awareness of the anticipatory phase should motivate firms to anticipate users' needs and recommend personalized travel sites or services. For instance, Yelp provides location-based recommendations to users based on the ZIP code listed by users. During a trip, firms can enhance tourists' experiences and create value by providing location-based, personalized information and interactive services [36]. Firms use beacons to enhance in-store or on-site experiences by providing coupons or adequate information that seem to attract tourists. Finally, firms should recognize the importance of the reflective phase by making it easy for tourists to share their experiences so that others can use the information in making their travel plans.

According to the process of tourists' experience by Tussyadiah and Fesenmaier [6], we present a flow chart of tourists' decision-making as it is affected by how firms shape the flow of information (Fig. 1). In the pretrip phase (anticipatory phase), users search for review information as the bases for their decisions on travel destinations and purchases. We suggest social distance from users, breadth of shared experience, and the valence of shared experience as important factors when users evaluate the information they encounter. After tourists make their decisions, they continuously compare what they are experiencing to the reported experience they earlier searched out. Depending on whether there is any discrepancy between the earlier shared experience they found and their actual experiences, tourists will decide whether to share their own experience information on a platform. Moreover, the quality of the experience itself will affect this decision. In the posttrip phase (reflective phase), users will first decide whether to share their experiences. Then, they may choose with whom they will share their experience. They may share their experience only with close friends or they may share it with the public through the platform that was the source of their earlier information. Finally, if they want to share, they will need to choose a medium. Some people upload only photos, but others write about their experiences along with photos.

Among the different phases of travel experiences, information exchanges occur in the pretrip and posttrip phases [6]. In the pretrip phase, travelers search for information to guide their purchases. For instance, Airbnb users review other traveler's comments and evaluations of accommodations. Moreover, they interact with the host to get more specific information. In the posttrip phase, travelers share their experiences through websites or mobile application. Airbnb recommends that its users leave comments and evaluations and reminds them to do so by sending them push messages. Thus, these shared experiences become an important source of information for future users who are at the starting point of the travel experience cycle. As mentioned before, users who share their experiences are the most important factor facilitating the growth of the STE through their freely sharing and creating travel information [40]. From the perspective of experience sharing, we analyzed how the major players in the STE manage experience information by users (Table 1). All four firms provide a platform for communication so that users can share their travel experiences. However, the way they shared experiences are demonstrated, and the medium of sharing travel experiences differs among firms. It is necessary to figure out the most effective way to promote tourists' sharing of their experiences to enhance decision-making by tourists.

3. Research model and hypotheses

This research comprises two parts. The first model describes decision-making by travelers based on shared experiences on a smart tourism platform such as Airbnb. The second model investigates how travelers make decisions on sharing their own experiences after travel. We created these two separate models to determine how travelers evaluate and use shared experiences and how a social community on a smart tourism platform grows in terms of the number of reviews. By investigating Model 1 and Model 2 simultaneously, we attempt to show the linear flow of experience information from a user's perspective. These two models are connected because the very behavior of sharing their travel experience is the result of an actual trip that was made using the other's experience information. Because the focus of this study is the sharing behavior of experience-related information on smart tourism platforms, both the response to shared experience in pretrip stage and sharing experience in posttrip stage are relevant in this study.

3.1. Model 1-decision-making based on shared experiences

Model 1 focuses on the anticipatory phase of travelers in which they search for and collect information based on experiences shared on a smart tourism platform. Experiences shared by other travelers exert a great influence on consumer behavior because consumers perceive them as more reliable than descriptions provided by firms [45,46]. For travelers to decide to make purchases, they should perceive experiences shared by other users as trustworthy and accept the information contained in their reviews. Thus, we suggest a research model as follows (Fig. 2).

Table 1
Major firms' management of experience sharing.

	Anticipatory phase			Reflective phase		
	Social distance	Review breadth	Valence	Share/No share	Target	Media
TripAdvisor	Show friends' comments and activities. Show friends' comments first	Text, image	5 stars	Provide community for sharing reviews	Public	Text, image
Yelp	Show friends' comments Send private messages to the specific user	Text, image	5 stars	Provide community for sharing reviews	Public, friends	Text, image
Airbnb	Send message to the host Show comments chronologically	Text	5 stars	Provide community for sharing reviews	Public	Text
Orbitz	Show comments anonymously	Text	5 stars (overall, categorical); recommendation%, rating of trip advisor	Provide community for sharing reviews	Public	Text

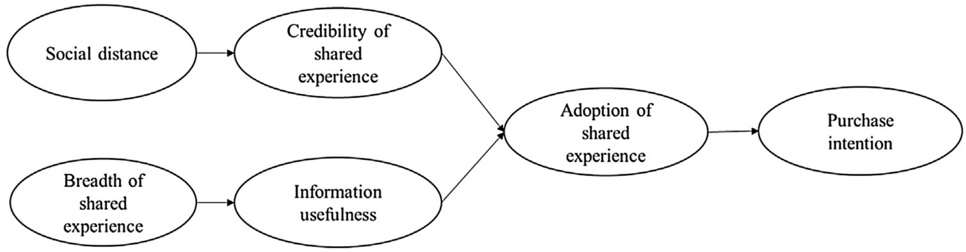

Fig. 2. Traveler's decision-making based on shared experiences.

In the process of making a purchase decision, travelers encounter diverse sources of experience information. According to Andreasen [47], there are four types of information sources: impersonal advocate (e.g., mass media), impersonal independent (e.g., consumer reports), personal advocate (e.g., sales clerks), and personal independent (e.g., friends). In the smart tourism context, travelers are mostly exposed to shared experiences from friends or from other travelers who usually leave reviews with personalized information. Research on sources of information alleges that personal or impersonal information sources influence decision-making of consumers depending on the sources' expertise and similarity to the seeker [48]. According to social identity theory [49], a similarity perceived by a user would increase trust by decreasing uncertainty [50,51]. Price and Feick [52] suggested that similarity between users will facilitate the flow of information because of a perceived ease of communication. Travelers who read shared experiences from similar users would find them more related and trustworthy [53]. Lo and Lie [54] argued that when there is trust in a relationship, the communicator is more likely to tolerate with less information richness. This is because trust derived from close social distance lowers the perceived level of risk, making people believe that there will be less possibility of loss in the interaction [55,56]. Therefore, close social distance will reduce the equivocality that users face when they try to discern shared information on a smart tourism platform. Thus, we can hypothesize that the social distance between a user (information seeker) and a personal reviewer would influence the credibility of a shared experience.

H1. Social distance between a user and a reviewer would influence the credibility of shared experience on a smart tourism platform.

How shared experiences are represented is also an influential factor in how travelers make their decisions. Travelers who share their experiences can convey travel information in more detail by providing detailed information that goes beyond accommodation itself. The breadth of shared experiences plays a vital role in the decisions travelers make. For instance, Airbnb users are expected to leave comments related to a specific topic, for example, housing. However, they can leave reviews regarding nearby restaurants or directions to the airport that increase the breadth of a review. Review breadth is beneficial because travelers gain information without additional search costs [57]. With more information from other travelers, travelers gain confidence in their decisions [58]. Moreover, broad information sharing on a smart tourism platform will reduce the uncertainty of users by providing more detailed descriptions so that travelers can imagine travel sites easier. Therefore, we can hypothesize that the breadth of shared experience would influence the perceived usefulness of shared experiences on a smart tourism platform.

H2. The breadth of shared experience would influence the perceived usefulness of shared experiences on a smart tourism platform.

For travelers to accept an experience shared on a smart tourism platform, they should trust it and regard it as a reference point for their decisions. Adoption of experiences shared by travelers is an important starting point because as travelers accept the information, they form a positive attitude toward travel destinations or accommodations. According to Harrison-Walker [59], acceptance of word-of-mouth (WoM) generates a positive attitude and increases the purchasing propensity of customers. The rate of acceptance of shared experiences differs according to the degree of trust receivers have toward the source of information. This is because in the face of uncertainty during the planning phase of travel, customers tend to rely on the trustworthiness of the information shared by others.

Credibility has a direct positive relationship with the adoption of shared experiences [27]. Credibility refers to the extent to which customers regard shared information as believable, true, or factual [60,61]. Customers who perceive an online shared experiences as credible have more confidence in accepting the information [60]. Thus, when customers consider the shared experiences are trustworthy, they are more likely to use them as references in making purchase decisions because of lessened equivocality [9]. Conversely, if shared experiences are not considered trustworthy, customers become risk-averse, avoiding the potential risk that may follow if they adopt and act on the information. Therefore, as travelers' perceived trust toward shared experiences increases, they are more likely to accept the information shared through a smart tourism platform.

H3. Credibility of shared experience is positively associated with the adoption of shared experiences on a smart tourism platform.

Perceived usefulness of a shared experience also plays a pivotal role in customers' adoption of shared experiences on a smart tourism platform. When there is perceived usefulness, users expect a positive use–performance relationship [62]. In the smart tourism context, based on our prior argument, the breadth of shared experiences leads to increased information usefulness. The breadth of shared experiences decreases the uncertainty that users encounter. With decreased uncertainty, users can enhance their problem solving in making reservations for a stay with reduced unpredictability [10]. Thus, information usefulness perceived by users facilitates the adoption of shared experience. Several empirical works reveal the direct relationship between perceived usefulness and users' adoption. Sussman and Siegal [63] showed that perceived usefulness has a mediating role between influence processes and information adoption. Schultz and Slevin [64] also understood the positive impact of "perceived effect of the model" on the adoption of a decision model. According to Davis [62], people's perceived usefulness does not necessarily reflect the objectivity of usefulness. In contrast, it is based on their subjective appraisal, which influences their adoption [62]. Thus, as long as travelers perceive shared information useful, their intention to adopt the information will increase. Although the equivocality of information provided by other users is reduced by the increased credibility of information from the closeness of a social relationship, uncertainty about the experience information can be reduced by the usefulness of information delivered through the increased breadth of the shared experience. With less uncertainty and equivocality attached to the information, users of a smart tourism platform would more willingly adopt the experiences shared by others.

H4. Information usefulness is positively associated with adoption of shared experiences on a smart tourism platform.

Experiences shared online can be considered as a type of social influence that affects the purchase decisions of customers. As useful external sources, shared experiences on a smart tourism platform enhance customers' purchase decisions in a way similar to the role of social influence theory [24]. Thus, customers who adopt shared information will make purchase decisions easily.

Adoption of a shared experience has a strong effect on a traveler's purchasing intentions. Propensity to adopt differs depending on the review valence (positive or negative). If a review contains positive statements, tourists are more willing to make purchases. Mayzlin and Chevalier [65] analyzed online reviews of books from Amazon and from Barnes & Nobles and found that positive online review resulted in the growth of sales. Similarly, Vermeulen and Seegers [66] argued that an exposure to positive reviews will increase tourists' consideration of purchasing by making them to form a positive attitude. On the other hand, when travelers are exposed to negative reviews, their willingness to make purchases diminishes. Basuroy et al. [67] found that both positive and negative reviews affect weekly box office revenues, but the impact of negative reviews diminishes over time, whereas the effect of positive reviews continues. In the short run, negative reviews have more influence on customers' purchase decisions, but then their influence is of short duration [67]. This means that in the short term, negative reviews have a greater effect on the perceived trust of customers, but positive reviews have more long-term impact. Thus, both positive and negative reviews will affect the relationship between adoption of shared experiences and purchase intentions.

H5. Adoption of shared experiences would influence purchase intention on a smart tourism platform.

3.2. Model 2-decision-making on sharing experiences

Model 2 describes how travelers shared their travel experiences proactively after their travels. We suggest two antecedents of travelers' intention to share their experiences that would help reduce the equivocality and uncertainty that other users confront. These are information discrepancy and the quality of actual experience (Fig. 3).

Consumers go through four-phases of learning, starting with hypothesis generation based on prior beliefs framed by information they researched [68]. This linear process is hypothesis generation → exposure to evidence → encoding of evidence → integration of evidence and prior beliefs. When customers actually experience a product or service, a case of information discrepancy occurs depending on the hypotheses or expectations established earlier. This information discrepancy can be either positive or negative but in either case, the gap between the expectation and actual experience matters when it comes to sharing experiences on a smart tourism platform.

According to the homeostasis utility perspective of WoM communication [69], customers seek balance after they make purchases and experience positive or negative feelings. After a positive purchasing experience, customers are willing to express their positive reactions [70]. By sharing their positive experiences, customers can ease their eagerness to express their joy, resulting in reduced tension [71]. However, when customers have a negative purchasing experience, they seek an outlet to express their anxieties [70]. By sharing negative experiences, customers can relieve their dissatisfaction by feeling a sort of catharsis [72,73]. Thus, to achieve a balance in their minds, travelers share their positive or negative experiences when a discrepancy occurs.

H6. As discrepancy of information increases, travelers would share their experiences on a smart tourism platform.

Experience sharing represents customers' loyalty or satisfaction [74]. This is related to the relationship between customers' perceived value and their satisfaction and their behavioral intentions [75]. Loyal customers who perceive great value from using products or services are more likely to recommend them to others such as their relatives, friends, or even strangers by spreading WoM [76]. In the tourism context, when tourists are satisfied with a travel destination, they become loyal by recommending it to others [77]. Chen and Chen [78] suggested direct relationships between satisfaction, experience quality, and positive behavioral intentions, which are partially supported. Thus, in this research, travelers who perceived their actual experience as high quality would proactively share their experiences.

However, when actual experience is disappointing, travelers share the negative information on a smart tourism platform. Among the motives for WoM communication behavior that Engel et al. [79] presented, concern for others is highly ranked. Users genuinely want to help their friends or other people to make a better purchase decision [79] by sharing their experience. Similarly, Sundaram et al. [70] suggested altruism as a major motivation, which describes users' desire to keep others from making the same mistake. Moreover, users tend to share their experiences to mainly reduce their anxieties and retaliate against the service provider [70]. In conclusion, when a quality that travelers experience deviates from a neutral state (either positively or negatively), travelers will share their experiences on a smart tourism platform.

H7. As the quality of actual experience deviates from the neutral, travelers would share their experiences on a smart tourism platform.

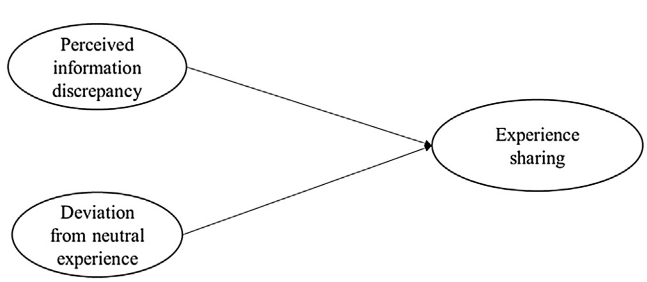

Fig. 3. Travelers' decision-making on sharing experiences.

4. Methodology

We conducted an experiment to empirically test research Model 1, which focused on the effects of social distance and review breadth on the anticipatory phase of travelers. The experiment allowed close control over independent, dependent, and possibly confounding variables to achieve a high degree of internal validity. A survey was used to examine research Model 2, which describes how travelers share their travel experience after their trip.

4.1. Participants

A professional survey company implemented the experimental process and the survey. Participants were recruited from ordinary people (not students) to enhance external validity. Subjects were drafted from the panel who met the following prerequisites: they must have travel experience; they must have a habit of examining other travelers' comments and evaluations of accommodations in the pretrip phase; they must have reservation experience through the Airbnb site; and they must have active Facebook accounts. Participation was voluntary, and all the participants received a five-dollar gift certificate for the purpose of increasing their motivation and involvement. Subjects were notified that they had to complete both the experiment and the survey to receive the gift certificate. After the experiment process was completed, survey data were collected, and a total of 411 subjects participated.

4.2. Experiment design for research Model 1

A 3 × 2 factorial design with two between-subject factors was used. The social distance factor had three levels (stranger, indirect friend, and direct friend), and the breadth of review factor had two levels (narrow and broad). Subjects were assigned randomly to six experimental groups (see Table 1). The average age of participants was 36.84 years, and 48% were male. In examining the homogeneity across the six groups, a Chi-square analysis revealed no significant differences in gender ($X^2 = 0.006$, $p = 0.940$). A one-way ANOVA assessment further ensured that no significant differences emerged between the groups in terms of age ($F = 0.177$, $p = 0.971$), propensity to trust ($F = 0.350$, $p = 0.883$), and product involvement (i.e., accommodations) ($F = 0.234$, $p = 0.948$).

We developed scenarios regarding travel experiences to represent one of the six experimental conditions. Subjects were asked to submit the name of a close friend on Facebook and also asked how often they visited their friend's timeline and how often they met in offline spaces. They were also required to imagine their next travel and provide information about where they expected to go, how long they expected to stay, and their expected budget. Subjects could imagine a more realistic situation with this anchoring of thought. To manipulate the breadth of review, two accommodation reviews were prepared. The broad review included not only lodging information but also information on transportation and nearby restaurants and shops. The narrow review had only lodging information. Social distance was manipulated by providing the name of a friend, the name of a friend's friend or the name of a stranger as the writer of the accommodation review. For example, their friend's name, which they provided at the beginning, actually appeared on the screen with the review for the direct friend group. Each scenario had two versions, and half of the subjects, regardless of groups, received reviews with a positive tone and the other half got reviews that were negative in tone. The differing effects of adoption of negatively and positively toned reviews on purchasing intention in research Model 1 were tested in Section 5.

To test research Model 1, four dependent variables were measured. Credibility of reviews is a measure of a user's belief that the review is believable, true and reliable, and was measured using three items from Pavlou and Dimoka [80]. Information usefulness measured a user's perception of the received information as valuable, thus enhancing their job performance. It was measured by three items borrowed from Sussman and Siegal [63]. Adoption of reviews, a process in which users purposefully engage in using review information [24], was measured by three items adopted from previous studies. Finally, users' purchase intentions were measured, using four items borrowed from earlier studies, to determine the likelihood that they would purchase the product [81].

As control variables, we measured participants' propensity to trust by using four items from Koufaris and Hampton-Sosa [82] and involvement by using three items from Suh et al. [83]. All dependent and control variables were measured using semantic differentials and seven-point Likert scales. These variables were operationalized using reflective items. Reflective items represented the effects of the construct under study, and each item reflected this construct [84]. Because each item reflected the same construct, the items should be correlated to each other, and they should exhibit adequate internal consistency. Appendix A lists all the measurements of this study.

4.3. Survey for research Model 2

Several hours after finishing the experiment, the same subjects participated in the survey. They were asked to fill out a demographic and travel experience questionnaire. Perceived information discrepancy was measured on salient attributes of accommodation services. Salient attributes are the most prominent and important attributes when consumers decide to buy products or services [85]. Through a review of lodging selection literature, we elicited five salient attributes of accommodation services—location, safety, services/staff, facility condition, and room cleanliness. Then the discrepancy was measured by the questions on these salient attributes borrowed from Suh and Chang [86]. The quality of actual experience of accommodations was measured by six items adopted from Kim Lian Chan and Baum [87]. The way subjects shared their travel experiences proactively after the trip was classified into three categories, namely sharing with close acquaintances, sharing through a SNS, and sharing through a travel app such as Airbnb and TripAdvisor, in passive to

Table 2
Descriptive statistics.

Treatment	Social Distance			Review Breadth	
Measurement	Stranger	Indirect friend	Direct friend	Narrow	Broad
Number of subjects	138	134	139	204	207
Credibility of reviews	4.39	5.31	5.17	4.81	5.11
	(1.09)	(1.07)	(1.07)	(1.22)	(1.06)
Information usefulness	4.69	5.21	5.07	4.73	5.25
	(1.16)	(1.13)	(1.09)	(1.21)	(1.02)
Adoption of reviews	4.57	5.30	5.07	4.79	5.16
	(1.25)	(1.13)	(1.23)	(1.31)	(1.14)
Purchase intentions	4.08	4.35	4.04	4.07	4.23
	(1.45)	(1.85)	(1.76)	(1.57)	(1.81)

Table 3
Interconstruct correlations: consistency, reliability, and discriminant validity tests.

	Composite Reliability	AVE[a]	SD	RB	CR	IU	AR	PI
SD	1.000	1.000	1.00					
RB	1.000	1.000	0.003	**1.000**				
CR	0.967	0.908	0.281	0.131	**0.953**			
IU	0.960	0.888	0.136	0.229	0.799	**0.942**		
AR	0.957	0.881	0.165	0.152	0.658	0.715	**0.938**	
PI	0.987	0.951	−0.009	0.046	0.287	0.287	0.139	**0.975**

SD: Social Distance, RB: Review Breadth, CR: Credibility of Reviews, IU: Information Usefulness, AR: Adoption of Reviews, PI: Purchase Intention.
[a] Average Variance Extracted.

Table 4
Loadings and cross loadings of constructs.

	SD	RB	CR	IU	AR	PI
SD	1.000	0.003	0.281	0.136	0.165	−0.009
RB	0.003	**1.000**	0.131	0.229	0.152	0.046
CR1	0.231	0.137	**0.944**	0.744	0.601	0.278
CR2	0.284	0.143	**0.964**	0.775	0.635	0.273
CR3	0.284	0.095	**0.951**	0.763	0.643	0.270
IU1	0.100	0.229	0.728	**0.926**	0.645	0.279
IU2	0.119	0.180	0.763	**0.952**	0.680	0.263
IU3	0.163	0.238	0.766	**0.949**	0.695	0.271
AR1	0.150	0.136	0.655	0.707	**0.922**	0.206
AR2	0.169	0.141	0.594	0.637	**0.949**	0.079
AR3	0.145	0.151	0.598	0.662	**0.944**	0.096
PI1	−0.024	0.07	0.298	0.299	0.145	**0.969**
PI2	−0.030	0.043	0.254	0.270	0.128	**0.978**
PI3	−0.005	0.035	0.284	0.278	0.131	**0.981**
PI4	0.025	0.03	0.280	0.272	0.136	**0.974**

aggressive order. Survey questionnaires are provided in Appendix A.

5. Results

5.1. Results for Model 1

The statistical analysis techniques applied to interpret data from the experiment were a structural equation model (SEM) using partial least squares (PLS) for hypotheses. To test our research model, we used a PLS-SEM, as implemented in SmartPLS version 3.2.3. and ANOVA analysis using SPSS for Windows 21.0. The results of the tests of the measurement models and the structural models from the PLS results are introduced below, followed by the results of ANOVA analysis. Table 2 summarizes the descriptive statistics.

As a check for manipulation, participants were asked about their perceptions of social distance and review breadth. In examining homogeneity across each treatment group, Chi-square analysis revealed significant differences in three social distance groups ($X^2 = 163.5$, $p = 0.000$) and two review breadth groups ($X^2 = 224.2$, $p = 0.000$). Close examination of each group revealed that the manipulations seem to be satisfactory except in the indirect friend group. The majority of the subjects in this group perceived an indirect Facebook friend (i.e., someone they did not know directly but was a friend of their friends) as a direct Facebook friend. This phenomenon might happen because the concept of SNS friends differed from that of real world friends. In a virtual world, people may perceive a friend of friends as their friend too. This is another interesting topic for future research. Thus, we ran two versions of statistical analysis, one for all the subjects assigned as in Table 1 and another for a smaller sample in which subjects with incorrect perception were removed. Both showed the same results for the hypotheses tests, so we report it here with full subjects.

5.1.1. Test of the measurement model

The social distance variable was dummy coded with Stranger as “1,” Indirect friend as “2,” and Direct friend as “3” and the review breadth variable was dummy coded with Narrow “1” and Broad “2” for the PLS analysis. Convergent validity was assessed by (1) reliability of items, (2) composite reliability of constructs, and (3) average variance extracted (AVE) [88,89]. The test of the measurement model for reflective constructs included individual item reliability, internal consistency, and discriminant validity.

In assessing internal consistency (reliability), composite reliability scores for every construct were well above 0.70, which is the suggested benchmark for acceptable reliability [88,90]. AVE measures the amount of variance that a construct captures from its indicators relative to the amount because of measurement error [91]. It should exceed 0.50 [89]. Table 3 shows that the AVE score for every construct satisfied this recommended minimum. Comparisons of the square root of the AVE (bold figures on the diagonal) with the correlations among the constructs indicated that each construct related more closely to its own measures than to those of other constructs; therefore, discriminant validity was supported [91]. An examination of cross-factor loadings, as shown in Table 4, also indicated good discriminant validity because the loading of each measurement item on its assigned latent variables exceeded its loading on any other constructs [91–93].

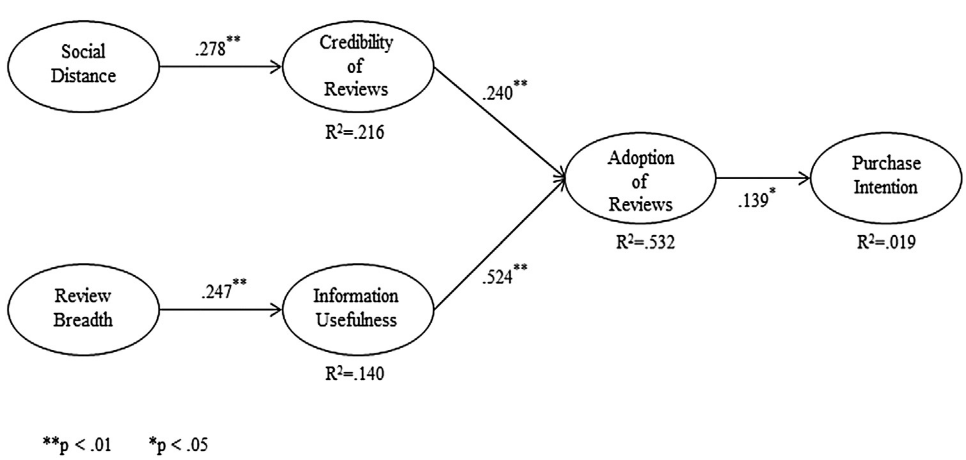

Fig. 4. Results of the structural model.

Table 5
Summary of PLS analyses.

Path	Beta	t	p
SD → CR	0.278	6.896	0.000
RB → IU	0.227	5.647	0.000
CR → AR	0.240	3.777	0.000
IU → AR	0.524	9.035	0.000
AR → PI	0.139	2.455	0.014

5.1.2. Test of the structural model and hypothesis testing

Fig. 4 and Table 5 graphically depict the PLS results, which show the standardized path coefficients among the constructs and the R^2 value for purchase intention. The bootstrap resampling method (500 subsamples) determined the significance of the paths within the structural model. The PLS analysis results in Fig. 4 show that all the hypotheses are supported; thus the proposed theoretical model in Fig. 2 is empirically supported. We hypothesized that social distance would increase the credibility of reviews (H1) and that review breadth would increase the information usefulness of reviews (H2). The results of the PLS analysis proved that social distance and review breadth produced positive effects on the credibility of reviews and information usefulness, with path coefficients of 0.278 ($p < 0.01$) and 0.247 ($p < 0.01$), respectively, thus supporting H1 and H2.

We hypothesized that the credibility of reviews and information usefulness would influence the adoption of reviews (H3, H4). Credibility of reviews and information usefulness had significant effects on the adoption of reviews with path coefficients of 0.240 ($p < 0.01$) and 0.524 ($p < 0.01$), respectively. Thus, H3 and H4 were supported. Hypothesis 5 was also supported because the adoption of reviews produced positive effects on the purchase intention. However, the adoption of reviews explained only 1.9% of the purchase intention. This is because the positive and negative valences cancel each other so that positive and negative reviews influence the purchase intention positively and negatively. Further analysis of the moderating effect of review valence is shown in the next section.

5.1.3. Moderating effect of review valence

A supplementary analysis of the existence of the moderating effects of review valence was performed. Moderator variables can be either metric or categorical in nature. Group comparisons, i.e., comparisons of model estimates for different groups of observations, can be regarded as a special case of moderating effects [95]. Once the observations are grouped, the model with the direct effects is estimated separately for each group of observations. Differences in the model parameters between the different data groups are interpreted as moderating effects [95]. To evaluate the moderating effect of usage experience, the research model was tested with the two subgroups of positive and negative reviews. As shown in Table 6, in Figs. 5 and 6, two different influence patterns are found for the two subgroups and reveal that review valence (i.e., positive vs. negative) moderates the relationship between the adoption of reviews and purchase intention.

The significance of difference in path coefficients between the subgroups of positive and negative reviews was calculated using the procedure described by Keil et al. (2000).

$$\text{Spooled} = \left[\frac{(Npositive-1)}{(Npositive+Nnegative-2)} \times SEpositive^2 + \frac{(Nnegative-1)}{(Npositive+Nnegative-2)} \times SEnegative^2\right]$$

$t = ((PC\quad Positive - PC\quad Negative))/([Spooled \times (1/(N\quad positive + 1/(N\quad negative))))$

where S_{pooled} = pooled estimator for the variance
t = t-statistics with $N_{positive} + N_{negative} - 2°$ of freedom
N = sample size of dataset for review valence
SE = standard error of path in structural model of review valence
PC = path coefficient in structural model of review valence

5.2. Results for Model 2

Model 2 investigated how perceived information discrepancy and the deviance from a neutral experience affected travelers'

Table 6
Results of moderating effect test.

	Full Sample	Positive Review	Negative Review	Difference Positive vs. Negative
	β	β	β	
Adoption of Reviews → Purchase Intention	0.139	0.786	−0.237	***

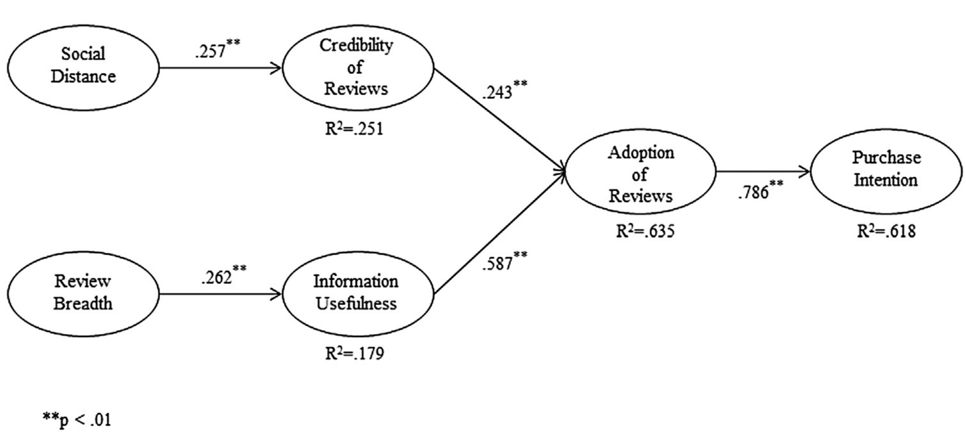

Fig. 5. Result of positive review group's structural model.

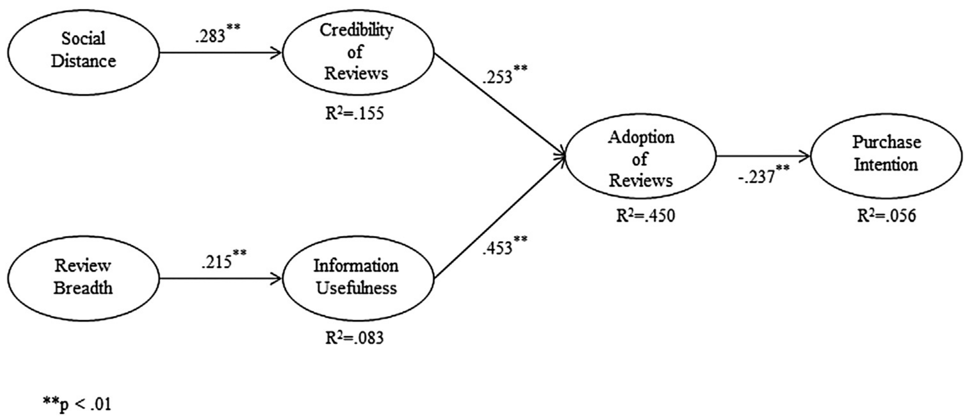

Fig. 6. Result of negative review group's structural model.

Table 7
Descriptive statistics and correlations.

Variable	Mean (S.D.)	1	2	3	4	5	6	7	8	9	10	11
Information discrepancy	3.29 (1.27)	1										
Quality positive	4.77 (2.11)	−0.37	1									
Quality negative	0.34 (1.00)	0.22	−0.76	1								
Age	3.30 (1.10)	0.06	−0.08	0.04	1							
Job	6.09 (5.06)	−0.11	0.07	0.03	−0.20	1						
SNS usage	3.26 (1.09)	0.05	0.00	0.01	0.06	−0.02	1					
WoM usage	5.61 (1.11)	−0.07	0.18	−0.07	−0.06	−0.01	0.22	1				
Info share online	2.27 (0.93)	0.13	−0.03	0.02	0.18	−0.18	0.52	0.22	1			
Exp share online	2.46 (1.05)	0.10	−0.03	0.01	0.13	−0.14	0.57	0.13	0.74	1		
Income	3.87 (1.22)	−0.01	−0.03	0.02	0.40	−0.15	0.04	0.10	0.18	0.13	1	
Education	2.17 (0.48)	−0.08	0.01	0.03	0.00	−0.02	0.00	−0.02	0.14	0.09	0.19	1

experience-sharing behavior on a smart tourism platform. Logistic regression was used because the dependent variable is binary, whether or not they shared their travel experiences on a smart tourism platform. We divided the sample into positive and negative experiences based on the valence of a shared experience. Table 7 shows the descriptive statistics and correlations among variables in the model. We controlled the demographic and personal characteristics of respondents such as sex, age, income, education, and job. In addition, we controlled respondents' usage of SNS and their normal use of WoM to clearly discern the antecedents of experience sharing on a smart tourism platform. Finally, respondents' general pattern of sharing information and experiences online were controlled so that we could rule out the effects of their normal propensities to share their experiences on a smart tourism platform.

In H6, we argued that as a perceived information discrepancy increases, travelers are more prone to share their experiences on a smart tourism platform. That is, either negatively or positively, travelers want to regain balance by sharing their experiences. The results showed that when travelers perceived their experiences as negative, they were more likely to share their experiences through a smart tourism platform, which is Airbnb in this experimental setting ($t = -2.02$, $p < 0.05$). Similarly, when their quality of travel experience was positive, they were more willing to share their experiences ($t = 3.47$, $p < 0.001$). Thus, H6 is supported, which argued that as information discrepancy increases, travelers share their experience information on a smart tourism platform.

Table 8
The effect of information discrepancy on experience sharing on a smart tourism platform.

	Positive experience	Negative experience
Information discrepancy	0.3556 (0.1025)***	−0.9376 (0.4651)*
Control variable		
Sex	−0.0380 (0.2507)	−0.1597 (0.9180)
Age	0.2462 (0.1232)*	−0.1701 (0.4751)
SNS usage	0.1472 (0.1449)	0.2556 (0.4047)
WoM usage	−0.1496 (0.1253)	0.0309 (0.3553)
Income	−0.0353 (0.1134)	0.2098 (0.4746)
Education	−0.0071 (0.2569)	−0.8699 (1.0430)
Job	−0.0210 (0.0255)	0.1987 (0.0891)*
Prior experience in sharing information online	1.2412 (0.2484)***	0.4849 (0.5443)
Prior experience in sharing experiences online	−0.2729 (0.1877)	0.4350 (0.5447)
Pseudo $\mathbf{R}^2$	0.1802	0.2935
LR χ^2	86.62***	16.16
N	350	44

Estimated standard errors are in parentheses. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 9
The effect of travel experience quality on experience sharing on a smart tourism platform.

	Positive experience	Negative experience
Quality	0.3553 (0.1611)*	−3.5151 (1.4733)*
Control variable		
Sex	−0.1246 (0.2471)	0.4454 (0.9816)
Age	0.2475 (0.1212)*	−0.0684 (0.4844)
SNS usage	0.1210 (0.1435)	0.0203 (0.4449)
WoM usage	−0.2302 (0.1219)	−0.3923 (0.3726)
Income	−0.0293 (0.1121)	1.5698 (0.7354)*
Education	−0.1093 (0.2524)	0.2424 (1.0683)
Job	−0.0363 (0.0250)	0.4247 (0.1571)**
Prior experience in sharing information online	1.3180 (0.2494)***	0.2570 (0.6041)
Prior experience in sharing experiences online	−0.2826 (0.1857)	1.1708 (0.7054)*
Pseudo $\mathbf{R}^2$	0.1644	0.3576
LR χ^2	79.00***	19.68*
N	350	44

Estimated standard errors are in parentheses. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

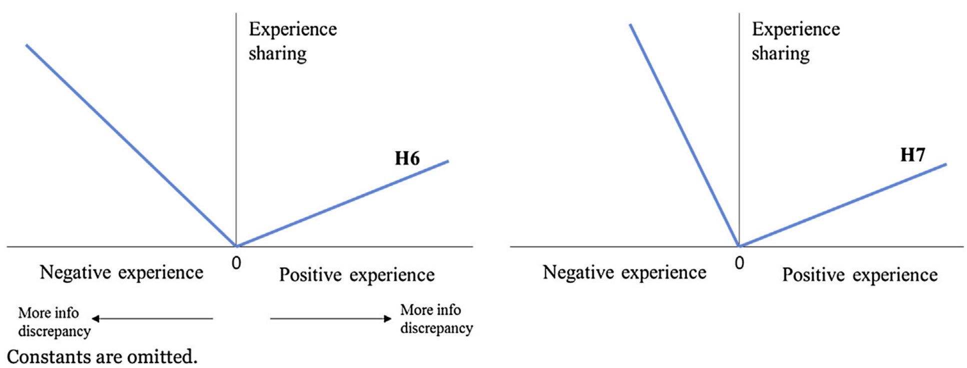

Fig. 7. Graphical results of Model 2.

Finally, H7 was supported, showing that the quality of a travel experience also affects travelers' propensity to share experiences on a smart tourism platform. When their travel quality was negative, travelers tended to share their experiences more ($t = -2.39$, $p < 0.05$). The result was the same when travelers rated their travels positively ($t = 2.21$, $p < 0.05$). To summarize, whether their experiences were positive or negative, travelers' propensity to share experiences on Airbnb increased. Tables 8 and 9 graphically depict the results of the logistic regression analyses of Model 2 and Fig. 7. As shown in Fig. 7, the absolute value of coefficients was greater when the travel experience was negative. This result indicates that a negative travel experience strongly outweighs a positive experience in its effect on travelers' propensities to share their experiences on a smart tourism platform.

6. Discussion

This study examined how travelers in the pretrip phase make their purchase decisions on a smart tourism platform on the basis of the experiences shared by others. Moreover, after their travels, we investigated how the quality of their travel experience and perceived information discrepancy affected their behavior in sharing their experience in the posttrip phase. The results of this study contribute to smart tourism research through its managerial implications on how firms should manage the flow of travelers' experience information and design smart tourism platforms to enhance travelers' purchasing and the growth of interactive platforms. This study also suggests a theoretical framework to explain how travelers make their decisions on a smart tourism platform by interacting with other travelers during phases of travelers' experiences within the perspective of information-processing theory.

All hypotheses were supported empirically. In the pretrip phase, social distance influences the credibility of shared experiences on a smart tourism platform by reducing the equivocality that travelers face in discerning information that is appropriate for them. As social distance lessens, users perceive shared reviews as trustworthy. Further analysis showed that Facebook friends and indirect Facebook friends have the same effect on the credibility of reviews (see Appendix B). Furthermore, breadth of shared experiences positively influenced information usefulness by decreasing uncertainty. That is, various information coupled with core information (which was lodging information in this context) made travelers think that the experience information was useful in their decision-making. Then, the credibility of shared experiences and information usefulness both positively affected the adoption of reviews by travelers. In turn, this adoption led to increased purchase intention. We conducted additional analysis to learn how review valence affects travelers' purchase intentions. Positive reviews increase the purchase intention but negative reviews decrease it. Thus, these two different effects are canceled out in a full sample.

In the posttrip phase, we investigated the effect of perceived information discrepancy and the quality of experience on travelers' propensity to share their experiences. The results indicated that as perceived information discrepancy increases, travelers are more prone to share their experience without regard to whether it was negative or positive. Similarly, travelers were more likely to share their experiences when the quality of their experiences deviated from neutral. These two results explain that as travel experiences go to an extreme in either direction (positive or negative), travelers tend to share their experiences.

The results of this paper have a theoretical implication in the explanation of how experiences shared on a smart tourism platform affect travelers' decision-making in accordance with the sequence of tourists' experience. By facilitating tourists' information processing that in turn enhances their problem-solving skills, social distance from the reviewer and breadth of shared experience on a smart tourism platform decrease the equivocality and uncertainty that tourists face. Furthermore, this study has managerial implications as well. There is a growing need for firms to manage huge amounts of information shared by their users through smart tourism platforms. Because user participation in sharing travel experiences is a core component within the STE, it is necessary for firms to design an interactive platform to increase the community, to enhance travelers' experiences, and to increase their purchases. The results of this study indicate that the presentation of reviews shared by direct and indirect friends positively affects travelers' adoption of reviews and increases their purchases. Thus, firms should first show shared experiences by users' direct and indirect friends in a platform based on the social network data they gathered. Moreover, specific guidelines are crucial for those travelers who want to share their experiences. For instance, when firms design an interactive platform, they can divide a review into sections, including housing, nearby restaurants, transportation, and impression of hosts rather than relying on users' discretion and initiative. Then, other travelers will adopt these reviews, thus increasing the likelihood that they will make purchases.

Moreover, to facilitate the growth of the user community in smart tourism, we suggest implementing two implications drawn from our second research model. Although both negative and positive experiences increase sharing of experiences, sharing of negative experiences is undesirable because it would negatively affect the purchase intention. Thus, the most important thing is to ensure to the fullest extent possible that travelers have a positive experience. In this effort, firms such as Airbnb can collaborate with other firms in the smart tourism field (e.g., smart destinations) to synchronize travel experiences. Furthermore, firms should try to decrease negative information discrepancies while increasing positive information discrepancies. Although our research did not capture the direction of the discrepancy, our results showed that "an unexpected thing" increases travelers' willingness to share their experiences, thus leading to the growth of the community on a smart tourism platform.

Several limitations need to be considered when interpreting the results of this research. First, we did not take into account whether the direction of an information discrepancy is positive or negative. Thus, it is unknown whether the reviews that travelers would like to share are positive or negative. Second, we did not capture the experiential phase of traveling. In smart tourism, interaction between travelers and a smart tourism platform occurs simultaneously as they travel. Then, a comparison of shared experience and actual experience occurs as travelers evaluate their experience and assess their level of satisfaction. However, because of the constraints of our research design, we had respondents reflect on their previous travels and make decisions on sharing their experiences.

In future research, it would be meaningful to capture the specific context of information discrepancies. This effort would yield detailed information that can be used to figure out the effect on sharing behaviors of travelers. Similarly, it is necessary to gain hard data regarding the target, review valence, and breadth of experiences travelers are going to share after they decide to share their experiences. The effect of price on the experience sharing suggested by Giannakos et al. [94] is another area we can pursue in future research.

Acknowledgement

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Appendix A. Questionnaires.

Construct: Credibility of Reviews

CR1: This accommodation review is likely reliable.
CR2: This accommodation review is likely truthful.
CR3: This accommodation review is likely credible.
Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

Construct: Information Usefulness
IU1: The information in this accommodation review is informative.
IU2: The information in this accommodation review is valuable.
IU3: The information in this accommodation review is helpful.
Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

Construct: Adoption of Reviews
AR1: After reading this accommodation review, my opinion about this facility became firmer.
AR2: After reading this accommodation review, I can easily decide whether to stay in this facility.
AR3: After reading this accommodation review, it is easier to decide whether to stay in this facility.
Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

Construct: Purchase Intention
How likely would you be to stay at this accommodation?
PI1: Unlikely 1 2 3 4 5 6 7 Likely
PI2: Improbably 1 2 3 4 5 6 7 Probably
PI3: Uncertain 1 2 3 4 5 6 7 Certain
PI4: Definitely Not 1 2 3 4 5 6 7 Definitely

Construct: Involvement
Please rate the process of choosing your accommodation:
IV1: Very unimportant decision/very important decision
IV2: Decision requires little thought/decision requires a lot of thought
IV3: Little to lose if I choose the wrong one/a lot to lose if I choose the wrong one

Construct: Propensity to Trust
PT1: It is easy for me to trust an accommodation review.
PT2: My tendency to trust an accommodation review is high.
PT3: I tend to trust an accommodation review, even though I have little knowledge of it.
PT4: Trusting an accommodation review is not difficult.
Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

Construct: Perceived Information Discrepancy
ID1: How much difference do you feel in judging the location of the accommodation when you compare the real experience and the Airbnb accommodation review?
ID2: How much difference do you feel in judging the safety of the accommodation when you compare the real experience and the Airbnb accommodation review?
ID3: How much difference do you feel in judging the services/staff of the accommodation when you compare the real experience and the Airbnb accommodation review?
ID4: How much difference do you feel in judging the condition of the facility of the accommodation when you compare the real experience and the Airbnb accommodation review?
ID5: How much difference do you feel in judging the room cleanliness of the accommodation when you compare the real experience and the Airbnb accommodation review?
ID6: How much difference do you feel in judging the overall experience of the accommodation when you compare the real experience and the Airbnb accommodation review?
Rarely Different 1 2 3 4 5 6 7 Very Different

Construct: Quality of Actual Experience
QE1: My accommodation experience was enjoyable.
QE2: The staff (or owner) of the accommodation was friendly.
QE3: My accommodation experience was something new.

QE4: My accommodation experience was comfortable.
QE5: My accommodation experience was safe.
QE6: My accommodation experience was informative.
Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

Appendix B. Further analysis for effect of social distance on the credibility of reviews.

Social Distance	Mean	SD	N	Subgroup at significance of 0.05 (Duncan test)	
				Group 1	Group 2
Stranger	4.39	1.10	138	O	
Indirect friend	5.32	1.07	134		O
Direct friend	5.18	1.07	139		O

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