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The Effect of Risk Perception on Behavior Towards "Untact" Tourism in Vietnam

Thao Nguyen Khuat[1] | Andrea Caputo[2,3] | Davide Serpico[4]

[1]Entrepreneurship & Innovation, EBS Universität Oestrich-Winkel, Oestrich-Winkel, Germany | [2]Department of Economics and Management, University of Trento, Trento, Italy | [3]SARChI in Entrepreneurship Education, Department of Business Management, University of Johannesburg, Johannesburg, South Africa | [4]Department of Philosophy, University of Milan, Milano, Italy

Correspondence: Andrea Caputo (andrea.caputo@unitn.it)

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ABSTRACT

Untact services have gained popularity across several areas of tourism as a fruitful strategy for companies in the recovery of tourism after the pandemic's outbreak. The notion of untact service denotes services in which consumers can avoid physical interactions thanks to advances in digital technologies. Through a combination of quantitative and qualitative analyses, this study investigates the impact of cognitive and affective risk perception on customers' behavior towards untact tourism in the Vietnamese context, which has recently seen a fifth wave of the pandemic. We adopted an extended version of the Theory of Planned Behavior (TPB), which unpacks people's decision-making into several psychological and behavioral components. The results of this study have several contributions to offer to behavioral literature and the potential to help businesses make informed decisions about their marketing and operations. This includes what actions and measures might be necessary to attract and retain customers in the post-pandemic environment.

1 | Introduction

The adverse impacts of the COVID-19 pandemic have been felt globally and have changed consumer behavior significantly, especially in the service sector. This is mainly due to the fear of infection risks (Bae and Chang 2021; General Statistics Office of Vietnam (GSO) 2021; Mogaji et al. 2022). Businesses and market researchers have since focused their attention on optimal policies and strategies for the upcoming future. In this context, the notion of *untact service* has been growing in popularity, together with the use of expressions like untact consumption, culture, marketing, recruiting, and election (Lee and Lee 2020). Untact service is seen as a fruitful strategy for companies working towards the recovery of tourism after the pandemic's outbreak (GSO 2022). Indeed, through untact service, consumers and personnel can avoid physical interactions thanks to advances in digital technologies (Bordoloi et al. 2018): automated dispensers, self-service counters and self-banking, online purchasing, and "unattended" kiosks are all examples of untact services that companies nowadays offer to attract new customers and, at the same time, reduce costs.

Although this represents a major concern for governments around the world, there is little research related to this topic; moreover, the literature on this topic is highly fragmented both graphically and in terms of time parameters. To fill this research gap, we investigated the impact of an unexpected global crisis, the COVID-19 pandemic, on risk perception and customers' behavior towards untact tourism. We consider this specifically in the Vietnamese context, which offers a highly relevant setting for examining tourism adaptation and resilience. Home to around 99 million people (GSO 2022), the country has rapidly developed into a top destination in Southeast Asia, with UNESCO World Heritage sites like Ha Long Bay and Hoi An, dynamic cities (e.g., Hanoi, Ho Chi

Minh City), and diverse natural attractions (e.g., Sapa, Phu Quoc). However, the COVID-19 pandemic severely disrupted this growth, international arrivals plummeted from 18 million in 2019 to just 3.8 million in 2020 (GSO 2021) due to health-related safety concerns. In response, Vietnam demonstrated effective crisis management and seized opportunities to promote domestic tourism, enhance digital transformation, and introduce contactless services (Van et al. 2020). These shifts, along with government-led "safe travel" initiatives, make Vietnam a timely case for studying untact tourism and post-crisis tourism innovation. Research on post-pandemic tourism would help businesses make more informed decisions about their marketing and operations. For instance, by considering how customers perceive COVID-19-related risk, businesses can better understand what measures might be necessary to attract and retain customers in the post-pandemic environment.

This research aims to examine how risk perception influences tourism-related behaviors during periods of unexpected crisis, with a specific focus on the adoption of contactless services in the Vietnamese tourism sector. This study investigates the dynamic relationship between perceived risk and behavioral adaptations among both consumers and service providers, ultimately seeking to develop strategic recommendations for the industry's resilience and innovation. From this objective, the following research question emerges: *How does risk perception during periods of unexpected crisis influence the adoption of contactless tourism services among customers and providers in Vietnam, and what strategic implications does this have for the industry's future development?*

To answer this research question, we adopt an extended version of the Theory of Planned Behavior (TPB) to examine how risk perception influences the adoption of contactless services in the Vietnamese tourism sector. Using a mixed-methods approach, we integrate quantitative survey data from 612 respondents with qualitative insights from in-depth interviews with tourism managers. This mixed-method strategy enables us to capture both consumer attitudes and business perspectives, providing a comprehensive understanding of behavioral adaptations to pandemic-induced risk perception.

This study makes several significant contributions to tourism and behavioral science literature. First, our study deepens theoretical understanding of risk perception by clearly distinguishing between cognitive and affective risk dimensions, an approach that remains underexplored in the context of untact tourism. While previous studies often treated risk perception as a unidimensional construct, our work highlights the importance of disaggregating rational evaluations from emotional responses, offering a more nuanced perspective on traveler decision-making. Second, the study contributes to the evolving discourse on pandemic-era tourism behavior by focusing on the later phase of the global crisis, a period characterized by behavioral adaptation, risk habituation, and the emergence of new travel norms. This contrasts with much of the existing literature, which primarily reflects responses during the early, more uncertain phases of the crisis. Third, by employing actual behavioral data rather than relying solely on self-reported intentions, the study enhances the empirical robustness of tourism research and delivers actionable insights for businesses seeking to foster resilience, technological adaptation, and service innovation in high-risk contexts.

2 | Literature Review and Hypotheses Development

2.1 | "Untact Tourism" and the Theory of Planned Behavior (TPB)

Untact tourism refers to a form of travel experience in which physical interactions between tourists and service providers are minimized or entirely replaced through the use of digital technologies and automated systems (GSO 2022). Rooted in the broader concept of "untact service," this approach leverages innovations such as self-check-in kiosks, AI-powered concierge systems, contactless payments, and app-based itinerary management to deliver seamless, technology-mediated touchpoints throughout the tourist journey (García-Madurga and Grilló-Méndez 2023). Accelerated by the COVID-19 pandemic, *untact tourism* has rapidly shifted from a niche convenience to a mainstream expectation, compelling destinations and hospitality operators to reimagine service delivery in ways that prioritize both safety and efficiency (Bae and Chang 2021). As *untact tourism* continues to reshape the travel landscape, understanding how tourists form attitudes and perceptions toward these technology-driven experiences becomes increasingly critical. In this regard, the Theory of Planned Behavior (TPB), originally proposed by Ajzen (1991), provides a well-established theoretical framework for examining the psychological factors that shape individuals' attitudes toward a given behavior.

In social sciences, numerous psychological factors have been explored and analyzed to predict and explain consumer behavior. The Theory of Planned Behavior (TPB) is one of the most widely used theoretical frameworks, especially in the unpredictable context of crises, such as the COVID-19 pandemic. This model was introduced by Ajzen (1991) as an extension of the Theory of Reasoned Action (TRA) postulated by Fishbein and Ajzen (1977). This comprises several interconnected constructs that explain human decision-making pathways and subsequent actions. Attitudes (AT), as defined by Manstead (2001), represent evaluative tendencies towards an entity with varying degrees of favor or disfavor. These are typically manifested through cognitive, affective, and behavioral responses.

Ajzen (1991) further elaborates that an individual's attitude toward an action reflects the extent to which they view the behavior positively or negatively. Thompson and Thompson (1996) characterize this as the evaluative measure of one's favorable or unfavorable assessment of the conduct in question. Subjective norms (SN) constitute the perceived social pressures or influences to engage in specific behaviors (Guo et al. 2024; O'Neal 2007). These norms reflect individuals' perceptions of how their reference groups would evaluate their engagement in particular actions or inactions. Perceived Behavioral Control (PB) encompasses an individual's subjective assessment of the ease or difficulty associated with executing a specific action or activity (Groot and Steg 2007). PB not only directly influences behavioral intentions but also plays a moderating role, as individuals with higher perceived control over behavior are more likely to develop strong intentions to perform it (Hagger et al. 2022).

Behavioral intentions (BI) represent the mediating factor between attitudes and actual behavior, where an individual's perspective regarding an item influences their intention to use it, which subsequently affects their actions (Rozenkowska 2023). BI is demonstrated to be strongly correlated with actual usage, making it a key predictor of user behavior (Esfandiar and Hadinejad 2025; Wu and Du 2012). While other factors may play a role in shaping behavior, their influences are largely mediated through BI, reinforcing its central role in decision-making processes (Davis et al. 1989; Guo et al. 2024). Finally, Behaviors (BH) represent the culmination of these factors, establishing that the most robust predictor of actual conduct is an individual's intention to act (Fishbein and Ajzen 2011; Villacé-Molinero et al. 2021). Accordingly, in the TPB framework, behavior is the ultimate outcome of the interplay between AT, SN, PB, and BI, highlighting the dynamic process through which psychological factors translate into observable actions.

2.2 | TPB Framework in the Tourism Sector

In the tourism sector, the TPB has been widely applied to explain travelers' decision-making processes, particularly in response to external factors such as safety concerns and uncertainties (Guo et al. 2024; Han et al. 2017). Indeed, with the global expansion of tourism, there has been an increasing focus on safety and potential risks associated with the travel experience (Liu et al. 2024). Since tourist choices often involve varying levels of perceived risk (Hüsser et al. 2024), we integrate risk perception into the TPB framework for a better understanding of how tourists assess potential threats and adjust their behavior accordingly. Risk perception is considered inherently *plastic*, meaning that people's experiences and perceptions of risk may vary across different sociocultural systems (Douglas and Wildavsky 1982) and can be shaped, modified, and integrated (Williams et al. 2022). This aspect has been a key concern in previous tourism studies (Pappas et al. 2021; Zhong et al. 2024). When deciding *where* to go and *how* to get there in the face of unknown dangers, travelers' decisions regarding destinations and modes of transport might be greatly impacted by concerns for their own safety (Chen et al. 2026). As a result of tourism's experiential and intangible nature, people tend to perceive risks as unpredictable and difficult to control (Chen et al. 2026; Fuchs et al. 2013). When individuals perceive that an activity poses a risk that exceeds their subjective threshold of acceptability, they may opt to forgo travel altogether (Hua et al. 2025).

2.3 | Hypotheses Development

In this study, building upon the work of Bae and Chang (2021), we classified risk perception through two main types including *Cognitive* and *Affective* risk perception. Cognitive Risk Perception (CR) refers to an individual's assessment of the likelihood that they would be exposed to hazards and threats (Reisinger and Mavondo 2005). This is a key component in health behavior theories, influencing how people respond to perceived threats (Chien et al. 2017; Li et al. 2024). For instance, during the pandemic, CR of individuals significantly impacted their engagement in preventive behaviors (Zhong et al. 2024). Affective risk perception (AR), in contrast, regards an individual's concerns or worries about their exposure to danger (Slovic et al. 2004). Its focus is on the emotional component of risk perception and how it influences a person's behavior, rather than its cognitive basis (Jeong et al. 2022). This style of information processing is rapid, intuitive, parallel, and spontaneous, and takes minimal cognitive effort (Lai et al. 2025). Given the effectiveness of TPB and the importance of risk perception in this context, our study extends this theoretical framework to include two new variables of risk perception to provide a comprehensive model for understanding the progression from attitudes to actual behavior, through various psychological and social mediators.

The relationships between risk perception and AT, SN, PB, and BI within the TPB model have been documented in previous research. Research indicates that risk perception significantly influences tourists' attitudes toward travel, as individuals evaluate potential dangers before making a decision. When risk perception is high, tourists are more likely to develop negative attitudes toward travel, associating it with uncertainty and potential harm (Williams et al. 2022). Conversely, individuals tend to have more positive attitudes, viewing travel as a safe and enjoyable activity with a low perception of risk (Zheng et al. 2021). Furthermore, perceived risk also affects SN, as individuals' travel decisions are influenced by the opinions and concerns of their social circles (Guo et al. 2024). If family, friends, or media portray travel as unsafe, individuals may experience social pressure to avoid it (Williams et al. 2022). On the other hand, if social groups emphasize travel safety as a necessity, individuals may feel more encouraged to engage in tourism despite potential risks (Fuchs et al. 2024).

In addition, PB over the travel decisions of individuals could be diminished by a high-risk perception, making them feel less capable of managing potential travel-related threats (Chien et al. 2017; Wang and Petrick 2025). In fact, when travelers perceive a destination as risky, they may feel unprepared to handle uncertainties, such as health threats, financial losses, or unexpected disruptions (Chen et al. 2026). This reduced confidence often leads to lower travel intentions, as individuals prioritize situations where they feel more in control (Huang et al. 2023). Ultimately, it is supposed that risk perception has a negative influence on BI, as individuals assess the risks and benefits of travel before making a final decision (Hüsser et al. 2024). Therefore, travelers may intend to postpone or cancel trips due to safety concerns (Yang et al. 2020). Based on these studies, we develop the first hypotheses, set as follows:

H1a. *Cognitive risk perception has a significant relationship with the attitude of customers in using untact tourism.*

H1b. *Affective risk perception has a significant relationship with the attitude of customers in using untact tourism.*

H2a. *Cognitive risk perception has a significant relationship with the subjective norms in using untact tourism.*

H2b. *Affective risk perception has a significant relationship with the subjective norms in using untact tourism.*

H3a. *Cognitive risk perception has a significant relationship with the perceived behavioral control of customers in using untact tourism.*

H3b. *Affective risk perception has a significant relationship with the perceived behavioral control of customers in using untact tourism.*

H4a. *Cognitive risk perception has a significant relationship with the behavioral intention of customers in using untact tourism.*

H4b. *Affective risk perception has a significant relationship with the behavioral intention in using untact tourism.*

Regarding core variables of the TPB model, AT, SB, and PB have been validated as powerful predictors of behavioral intention and actual behavior in tourism (Ulker-Demirel and Ciftci 2020; Rozenkowska 2023; Liu and Park 2024). For instance, Qiu et al. (2022) extended the TPB by incorporating environmental awareness and sustainable destination images, finding that these factors significantly influence tourists' intentions toward sustainable tourism. Similarly, Wang and Petrick (2025) integrated self-congruity theory with TPB and demonstrated that these factors significantly influence tourists' pro-environmental behavioral intentions in heritage tourism. More recently, a study by Liu et al. (2024) explored tourists' intentions to engage in digital-free tourism experiences and highlighted the predictable roles of tourists' AT, SN, and PB over their ability to disconnect. Another study by Liu and Park (2024) investigated how metaverse tourism experiences influence actual travel intentions and confirmed the roles of these variables in shaping tourists' real-world travel intentions and behaviors. Research also explored the mediating role of BI between these three variables and actual behavior—the final action of the decision-making process. When a person has high intentions for an action, it is more probable that they will carry it through (Ajzen 1991; Wu et al. 2021). From the previous research, the following hypotheses are developed:

H5. *Attitude has a significant relationship with the behavioral intention of customers in using untact tourism.*

H6. *Subjective norm has a significant relationship with the behavioral intention of customers in using untact tourism.*

H7. *Perceived behavioral control has a significant relationship with the behavioral intention of customers in using untact tourism.*

H8. *Behavioral intention has a significant relationship with the behavior of customers in using untact tourism.*

Taken together, these two sets of hypotheses reflect the theoretical model represented in figure 1, which was originally proposed by Bae and Chang (2021).

Bae and Chang (2021) investigated a similar research question to ours, namely, the impact of risk perception on behavioral intention towards untact tourism in the early stage of the pandemic in Korea. Our aim is to evaluate this issue in a different context and period, that is, the fifth wave of the pandemic in Vietnam. Moreover, the model of Bae and Chang (2021) did not consider "Behavior" (BH) as a central component to be investigated. Including this variable in the analysis seems important to assess how people's *actual* behavior is influenced by risk perception, AT, SN, and PB.

3 | Methods

This study focuses on Vietnamese tourism, which is one of the fastest-growing tourism markets in Southeast Asia and experienced severe disruptions during the pandemic (GSO 2021). This has resulted in increasing health concerns and changes in consumer behavior. The rise of untact tourism—which leverages digitalization, automation, and self-service options—became a key strategy for both businesses and travelers seeking safer alternatives (Ghaderi et al. 2022). Given Vietnam's widespread smartphone usage, advanced e-commerce infrastructure, and government-led digital transformation initiatives (International Trade Administration 2021), untact tourism emerged as a viable solution. This context makes for a compelling study that we might better understand how risk perception influences travel behavior and how businesses can enhance their performance after a disruption.

Our research design makes use of a sequential mixed-methods approach of data collection and analysis, involving both quantitative and qualitative methodologies. This approach is supported by pragmatic and theoretical considerations, among which is the belief that a combination of different methods would provide a more comprehensive understanding of this complex research topic (Nastasi et al. 2010). Initially, we employed Structural Equation Modeling (SEM) for quantitative analysis to examine the relationships between variables. SEM is a multivariate statistical technique that enables the simultaneous examination of multiple dependent relationships while accounting for measurement errors (Maruyama 1997). The technique is well-suited to this study as it allows for comprehensive model testing, incorporating direct and indirect effects among variables in a complicated research model (Hoe 2008). Additionally, SEM provides robust model fit evaluation using indices like comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA), ensuring the validity of the findings.

Based on the literature review and the research model (Figure 1), a questionnaire survey was developed with a 5-point Likert scale derived from Gebretsadik et al. (2021), Tadese et al. (2021), and Wong et al. (2020), in their pioneering recovery study. The recovery dimension scales were adjusted to apply to the Vietnamese tourism market. This includes 49 items that were used in this study to measure 7 variables. The survey was conducted by the authors between January and April 2022 through Google Forms on consumer forums, as well as traveling fan pages on Facebook and other personal connections of the authors to get a wider reach.

This period marked the fifth wave of the pandemic in Vietnam when vaccines were released and widely deployed, and people were equipped with a certain amount of knowledge related to the epidemic (World Bank 2023). In addition, this also presents a "new normal" transition, whereby society expects restoration of daily life with minimal disruption. This phase notices the significant shifts in customer awareness and behavior as they remained cautious after the epidemic, while simultaneously expressing high demand for social activities, especially tourism, after a long period of restriction (Nguyen-Anh et al. 2023). To calculate the appropriate sample size, we followed the method proposed by Hair et al. (2012). The ratio of the number of observations to one variable (k) is: 5/1 or 10/1. The formula to determine the minimum sample size for the model is as follows:

$$n = 10 * \sum_{j=1}^{m} p$$

where n: minimum sample size, m: total items built for each variable in the questionnaire, p: total observed variables in the research model.

The research model has 7 observed variables; each variable has 7 items in the measured scale, choose k = 10/1, then the minimum sample size is:

$$n = 10 * \sum_{j=1}^{7} 7 = 490 \text{ (respondents)}$$

The final count resulted in 986 respondents and 612 usable values. These were input into the SPSS software with the AMOS package to analyze after filtering out the space and missing values. The sample shows no significant difference between male and female respondents. Most participants are young (18–35 years old) and have a regular monthly income. Their marital status is diverse, with more than half being married, while the rest are either single or in a stable relationship. The main level of education of the sample is college or university; nearly 60% had a bachelor's degree, followed by postgraduate and high school.

The use of qualitative methods in the second phase of the research helped us to elaborate, enhance, clarify, confirm, and illustrate the findings from the quantitative phase. A semi-structured interview was conducted by the authors between May and June 2022 with five participants from different companies for insightful qualitative methodology (Yin et al. 2019). Interviews were conducted virtually to accommodate ongoing COVID-19 safety measures and lasted approximately 45–60 min each. The qualitative data collected have been then analyzed through the MAXQDA software (Rädiker and Kuckartz 2020).

4 | Analysis of the Results

4.1 | Quantitative Analysis

4.1.1 | Reliability Test Analysis

All seven factors in the reliability analysis, including CR, AR, AT, AN, PB, BI, and PH, have Cronbach's Alpha values greater than 0.5. The values of Cronbach's Alpha and F-test Sig. for all

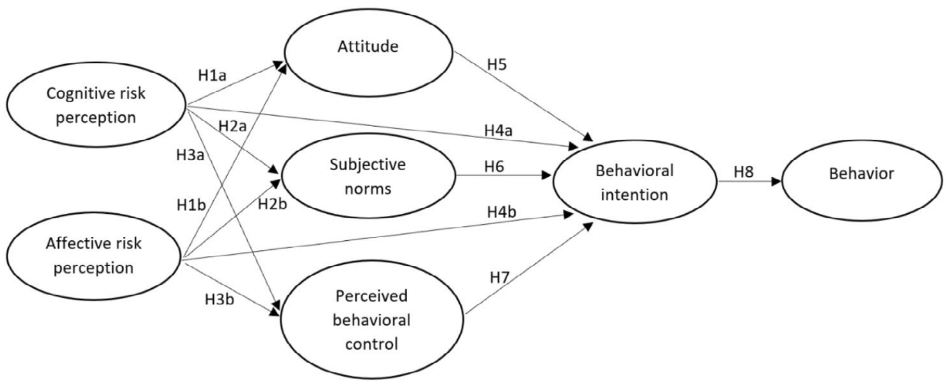

FIGURE 1 | Research model (adapted from (Bae and Chang 2021)).

TABLE 1 | Results of the reliability test.

Variables	Cronbach's Alpha	Mean	Variance	F	Sig.
CR	0.824	3.689	0.057	65.770	0.000
AR	0.914	3.919	0.002	6.418	0.000
AT	0.649	3.686	0.215	156.715	0.000
SN	0.803	2.812	0.055	46.689	0.000
PB	0.924	3.492	0.011	22.440	0.000
BI	0.667	2.901	0.025	17.101	0.000
BH	0.926	2.279	0.004	8.231	0.000

Note: AR, affective risk perception; AT, attitudes; BH, behaviors; BI, behavioral intention; CR, cognitive risk perception; PB, perceived behavioral control; SN, subjective norms.

variables are also validated (see Table 1). This means that the items in the questionnaire used to measure the six factors in the research model have good internal consistency and are closely correlated with each other.

4.1.2 | Exploratory Factor Analysis (EFA)

46 out of 49 items correlated equal to or more than 0.3 with at least one other item, indicating reasonable factorability. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.917, which is above the recommended value of 0.6. The Bartlett's test of sphericity was significant ($\chi 2$ (1106) = 1902.295, $p < 0.05$), and the commonalities were all above 0.5, indicating that each item shared some common variance with other items (Fabrigar and Wegener 2012) (Table 2). Based on these results, factor analysis was deemed suitable for all 49 items.

After conducting an EFA on all seven variables (including dependent and independent variables), a total of six items were eliminated because they did not contribute to a simple factorial structure and had a primary factor loading below 0.4. These items are CR2, AT4, AT5, SN5, BI2, and BI6 (see Table 3).

Advancements in factor analysis and structural equation models have pointed out that EFA includes error in the correlation between variables, while CFA does not (i.e., error is a separate term in the equation) (Marsh et al. 2014). Thus, we used CFA after EFA to gain a better validity determination of the model.

4.2 | Confirmatory Factor Analysis

We ran the models, for goodness-of-fit statistics analysis, respectively from one- to seven-factor model to identify the best model for analysis. The goodness-of-fit statistics were obtained after the models were estimated. The seven-factor model has the lowest RMSEA, AIC, and BIC values (see Table 4). Furthermore, CFI and TLI, which should ideally be greater than 0.9 (Barrett 2007), are lower for all the examined models except for the seven-factor model. Thus, the seven-factor model appears to be the best model to be further analyzed.

Regarding the Confirmatory Factor Analysis estimates, Table 5 shows the estimated value of each item; these values should be equal to or more than 0.5 to express the consistency with the factor, and the *p*-value should be less than 0.05 to be validated.

TABLE 2 | Results from the KMO and Bartlett's test.

Kaiser-Meyer-Olkin measure of sampling adequacy		0.917
Bartlett's test of sphericity	Approx. Chi-Square	1902.295
	df	1106
	Sig.	0.000

The CFA estimates increase the level of significance when eliminating the items from the factors. The estimated value of six factors (CR2, AT4, AT5, SN5, BI2, and BI6) is lower than 0.5, while the *p*-value was higher than 0.05.

4.3 | Structural Equation Modeling Analysis and Hypothesis Testing

Table 6 shows the analyzed results from 43 selected items for the research model.

- *Chi-square test ($\chi 2$)*: The $\chi 2$ test would be excellent for optimal fitting of the chosen SEM, with $\chi 2$/df ratio less than 3 and *p*-value less than 0.05 (Kline 2016). The result shows that $\chi 2$/df equal to 2.062 and *p*-value = 0.000, which indicates acceptance for this structural model.
- *Root means square error of approximation (RMSEA)*: RMSEA is more sensitive to sample size than the $\chi 2$ test and is excellent for discovering model misspecification fitting (Chen et al. 2010). Following (Kline 2016), the ideal value of RMSEA is less than 0.05 and in this model, this value is equal to 0.042, which is arguably a significant result.
- *Comparative fit index (CFI)*: The CFI's value varies from 0.0 to 1.0 and in reality, the CFI should be near to or greater than 0.95 (Hu and Bentler 1999). The CFI analyzed above is 0.951 > 0.95, which is significant for the model.
- *Tucker-Lewis's index (TLI)*: According to (Kline 2016), a TLI of > 0.90 is considered acceptable. In this research analysis, the value of TLI is 0.947, which shows the validity of the model.

Statistically, the hypotheses are validated only if the *p*-value is less than 0.05. Because the *p*-values are higher than 0.05, there is not enough evidence to prove the relationship between variables of hypotheses 1b, 2b, 3b, and 4b. In other words, this analysis cannot confirm a significant relationship between AR and other variables (AT, SN, PB, and BI). Other hypotheses, however, are supported and show positive linear regression relationships (see the Discussion for further details) (Table 7).

The linear relationships between variables are shown in Figure 2. Here, the dashed arrows indicate rejected hypotheses, while the solid arrow line shows the supported hypotheses with statistical indicators in the research model.

4.4 | Qualitative Analysis

Between May and November 2022, we conducted in-depth interviews with 5 participants with managerial positions in their companies and with 3.5–7 years of experience in tourism-related sectors. The area and target market are in the popular tourist destinations of Vietnam such as Da Nang, Ha Long, and Nha Trang. The interviews covered a variety of topics relating to the company's response to the pandemic, ranging from planned management strategies to the development of new products and services, as well as challenges that the company had to face and recommendations for future businesses.

TABLE 3 | Component matrix.

	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7
CR1	0.611						
CR2	**0.056**						
CR3	0.609						
CR4	0.561						
CR5	0.632						
CR6	0.645						
CR7	0.624						
AR1		0.732					
AR2		0.783					
AR3		0.757					
AR4		0.825					
AR5		0.834					
AR6		0.812					
AR7		0.810					
AT1			0.613				
AT2			0.690				
AT3			0.632				
AT4			**0.032**				
AT5			**0.002**				
AT6			0.634				
AT7			0.648				
SN1				0.525			
SN2				0.508			
SN3				0.558			
SN4				0.471			
SN5				**0.072**			
SN6				0.587			
SN7				0.601			
PB1					0.555		
PB2					0.562		
PB3					0.578		
PB4					0.591		
PB5					0.535		
PB6					0.571		
PB7					0.600		
BI1						0.547	
BI2						**0.122**	
BI3						0.616	

(Continues)

TABLE 3 | (Continued)

	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7
BI4						0.568	
BI5						0.625	
BI6						**0.015**	
BI7						0.576	
BH1							0.518
BH2							0.494
BH3							0.456
BH4							0.513
BH5							0.518
BH6							0.515
BH7							0.516

Note: Extraction method: Principal component analysis. The items highlighted in bold indicate those that did not contribute to a simple factorial structure. A comprehensive list of these items can be found in the accompanying script.

According to the responses of the participants, although all companies have been heavily affected by the COVID-19 pandemic, not all companies have well-structured contingency plans to implement immediately after social distancing regulations were developed to confront the pandemic. Results are shown in Table 8.

4.4.1 | Response to COVID Pandemic and Specific Strategies

Most of the participants shared plans about digitalization, particularly moving online for activities such as internal communications, meetings, marketing, and sales activities. In addition, cutting down staff or switching to short-term labor is also a widely applied strategy to limit the costs for the company. Besides, some other methods are applied, such as applying for government aid packages, saving costs, and focusing on customer relationship management during the pandemic.

Digitalization as well as promotions and discounts for customers have been specifically prioritized. Short-term goals and market research are gaining attention so that companies can achieve more effective results and evaluate growth strategies in the near future when we consider the possibility of sudden disruptions.

4.4.2 | New Products and/or Services and Their Performance

During the pandemic, the sales were mainly aimed at minimizing the interactions between customers and sellers to ensure the health and safety of customers and staff. Those included automation machines, self-services, shifting from traditional sales to online sales, or adjusting the menu to better suit the new demands of customers. Those new products or services are mostly built from market research or customer contributions. Initially, they were not effective in terms of business, but the companies still received positive feedback from the customers who have experienced such products and services. As a result, these changes have had a positive impact on the company's subsequent growth.

4.4.3 | Strategy Evaluation and Recommendations

Strategies or actions that were undertaken by companies had both strengths and weaknesses. The primary observable weakness is the limited budget. The losses during the pandemic period meant that managers did not have the budget to carry out the innovation of products. Following this, even if the demand of the customers was large, the companies did not always have the availability of goods and services to meet such demand, which led to lost sales. Finally, when converting from traditional business to online sales, the problem of counterfeit goods is also a real concern, as it can affect a brand's reputation, thereby directly affecting productivity as well as official distribution company sales.

However, these strategies saved a significant amount of money for the company. The reduction of employee numbers or the launch of new products and services more closely related to customer needs has allowed the companies to operate more effectively, gain a competitive advantage in differentiation, and diversify products. Especially relevant are improvements in the process of reaching customers and enhancing brand equity, as well as strengthening customer relationships.

Based on practical experience and results, the interviewed managers gave recommendations that can be applied in case of future disruptions. These include transforming to digitalization, focusing on innovation, and adopting active and flexible management to "improvise" in case of contingencies. As for the implementation of strategies, measurement, assessment, and risk management should also be carried out in parallel.

TABLE 4 | Results for goodness-of-fit statistics for all models.

	1-factor model	2-factor model	3-factor model	4-factor model	5-factor model	6-factor model	7-factor model
χ2/df	11.717	Unidentified	Unidentified	Unidentified	4.542	4.544	1.72
RMSEA (90% CI)	0.132	0.159	0.159	0.159	0.076	0.065	0.034
AIC	13498.837	2450	2450	2450	5289.615	4168.644	2140.295
BIC	13525.041	7860.497	7860.497	7860.497	5766.623	4663.318	2665.886
CFI	0.338	Unidentified	Unidentified	Unidentified	0.783	0.845	0.956
TLI	0.309	Unidentified	Unidentified	Unidentified	0.772	0.836	0.954

Note: AIC, Akaike's information criterion; BIC, Bayesian information criterion; CFI, comparative fit index; CI, confidence interval; Df, degrees of freedom; RMSEA, root mean square error of approximation; TLI, Tucker-Lewis's index.

TABLE 5 | Factor estimates with maximum likelihood estimates.

	Estimates	S.E.	C.R.	*p* value
CR7 ← CR	1.000			
CR6 ← CR	1.007	0.032	31.652	***
CR5 ← CR	0.977	0.033	29.608	***
CR4 ← CR	0.878	0.037	24.061	***
CR3 ← CR	0.939	0.034	27.581	***
CR2 ← CR	**0.128**	**0.084**	**1.516**	**0.130**
CR1 ← CR	0.945	0.033	28.216	***
AR7 ← AR	1.000			
AR6 ← AR	0.946	0.043	21.842	***
AR5 ← AR	1.008	0.045	22.444	***
AR4 ← AR	0.988	0.044	22.571	***
AR3 ← AR	0.919	0.048	18.975	***
AR2 ← AR	0.977	0.046	21.093	***
AR1 ← AR	0.791	0.043	18.334	***
AT7 ← AT	1.000			
AT6 ← AT	0.965	0.036	26.612	***
AT5 ← AT	**0.021**	**0.088**	**0.235**	**0.814**
AT4 ← AT	**0.012**	**0.089**	**0.139**	**0.889**
AT3 ← AT	0.977	0.036	26.996	***
AT2 ← AT	1.007	0.034	29.304	***
AT1 ← AT	0.955	0.036	26.419	***
SN7 ← SN	1.000			
SN6 ← SN	1.006	0.044	25.127	***
SN5 ← SN	**0.038**	**0.073**	**21.825**	**0.601**
SN4 ← SN	0.926	0.045	25.414	***
SN3 ← SN	0.870	0.044	24.819	***
SN2 ← SN	0.842	0.043	25.571	***
SN1 ← SN	0.848	0.043	19.671	***
PB7 ← PB	1.000			
PB6 ← PB	0.964	0.038	22.932	***
PB5 ← PB	0.917	0.042	21.851	***
PB4 ← PB	0.886	0.035	20.453	***
PB3 ← PB	0.957	0.039	19.791	***
PB2 ← PB	0.993	0.039	19.764	***
PB1 ← PB	0.839	0.043	19.668	***
BI7 ← PI	1.000			
BI6← PI	**0.130**	**0.101**	**1.287**	**0.198**
BI5 ← PI	1.173	0.068	17.246	***

(Continues)

TABLE 5 | (Continued)

	Estimates	S.E.	C.R.	*p* value
BI4 ← PI	1.143	0.066	17.444	***
BI3 ← PI	1.273	0.068	18.795	***
BI2 ← PI	**0.225**	**0.098**	**2.301**	**0.021**
BI1 ← PI	0.955	0.061	15.662	***
BH7 ← BH	1.000			
BH6 ← BH	0.995	0.036	27.536	***
BH5 ← BH	0.890	0.036	24.530	***
BH4 ← BH	0.999	0.036	27.413	***
BH3 ← BH	0.869	0.034	25.504	***
BH2 ← BH	0.950	0.042	22.772	***
BH1 ← BH	0.838	0.041	20.483	***

Note: The bold values represent items with estimated values less than 0.5 and *p*-values greater than 0.05. A complete list of these items is also available in the script.

TABLE 6 | Model indicators from SEM analysis.

χ^2/df	Probability level	RMSEA (90% CI)	CFI	TLI
2.062	0.000	0.042	0.951	0.947

5 | Discussion and Conclusions

5.1 | Discussion

We investigated the relationship between *cognitive* and *affective risk perception* (CR and AR) and core variables within the TPB framework (*attitudes, subjective norms, perceived behavioral control, behavioral intention*, and *behaviors*) in an unexplored context, namely the use of untact tourism in Vietnam during the fifth wave of the COVID-19 pandemic.

Firstly, the set of hypotheses H1a, H2a, H3a and H4a expected significant relationships between CR and AT, SN, PB, and BI. Our results support these hypotheses, which were also confirmed by previous studies (Ajzen 1991; Bae and Chang 2021; Barrett and Feng 2021; Long and Khoi 2020; Van et al. 2020). This finding means that individuals who perceive higher cognitive risks are more likely to develop cautious attitudes, be influenced by social norms, feel a greater need for control over their travel decisions, and ultimately exhibit stronger behavioral intentions toward untact tourism as a safer alternative. In fact, during the pandemic, some people had proactively avoided prospective losses and had a more cautious attitude towards the disease outbreak than others (Zhong et al. 2024). For such people with higher cognitive perceived risk, activities involving untact tourism would be particularly attractive during the economic recovery and individuals would be more supportive and involved in this type of travelling (Liu et al. 2024). Moreover, after the global crisis, activities gradually reopened with measures to ensure safety for customers' health (Villacé-Molinero et al. 2021). Accordingly, when tourists perceive that the benefits outweigh the risks from the use of services, the greater the cognitive perceived risk of individuals, the more willing they are to engage in the use of those services. This supports the argument that risk perception does not always deter engagement but can instead drive interest in alternative, safer tourism formats, especially during periods of heightened uncertainty and economic recovery (Lobb et al. 2007; Sterman and Dogan 2015; Yang et al. 2021).

Secondly, regarding the set of hypotheses on AR (H1b, H2b, H3b, and H4b), the results do not support our initial hypotheses, revealing no significant relationship between AR and other variables in the research model. Although the results are inconsistent with our hypotheses, the findings are in line with previous studies (Chen et al. 2026; Loewenstein et al. 2001; Schmiege et al. 2009), which highlight the responses of affective perception to risk. For example, fear or anxiety is highly subjective and does not always influence behavioral change, especially when individuals have adapted their emotional responses during a long period of crisis (Miao et al. 2022; Slovic 2000). High AR, in a traditional view, is strongly associated with avoidance intention (Jeong et al. 2022; Sheeran et al. 2014; Slovic et al. 2004). Interestingly, however, our results suggest that a high perception of AR does not lead to changes in intention to use untact tourism. This is because, based on an acceptable level of internal risk perception, people tend to regulate their behaviors accordingly (Dryhurst et al. 2022). Indeed, in the fifth wave of the pandemic, familiarity with the virus, vaccine coverage, and government safety measures may have reduced emotional sensitivity to risk, leading individuals to perceive untact tourism as a manageable alternative rather than an avoidance trigger.

Additionally, research from Pyszczynski et al. (2021) indicates that when individuals repeatedly confront mortality threats, they may develop psychological resilience, resulting in behavioral normalization over time. Similarly, Stechemesser et al. (2023) also suggest that prolonged exposure to health threats leads to emotional desensitization and behavioral normalization. Aligning with these studies, it can be said that, as travelers in Vietnam had already adapted to the presence of COVID-19, the psychological salience of risk emotions has been reduced in their decision-making process. Our findings are in contrast with the similar research of Bae and Chang (2021), which was employed during the second wave of the pandemic and pointed out that AR has a strong impact on AT, SN, PB, and BI. In this period, uncertainty surrounding vaccine efficacy and the emergence of new variants intensified fear-based decision-making, reinforcing the impact of affective risk on behavioral responses. This difference has highlighted the context-dependent nature of the TPB (Ajzen 2011; Han et al. 2017) and involves the role of risk perception over time (Zhong et al. 2024).

Thirdly, our results support hypotheses H5, H6, H7, and H8, showing that AT, SN, and PB positively influence BI, while BI, in turn, positively affects BH. These findings are consistent with earlier TPB studies' findings, such as Huang et al. (2020) and Huang et al. (2014), where people's BI toward untact services were influenced by their assessment of the activity, identification based on the community's culture, and the

TABLE 7 | Results of causal relationship analysis.

Hypothesis	Causal relationship	Estimate	S.E.	C.R.	*p*-value	Hypothesis testing
1a	AT ← CR	0.610	0.042	14.537	***	Supported
1b	AT ← AR	0.037	0.044	0.839	**0.401**	Not supported
2a	SN ← CR	0.305	0.054	5.646	***	Supported
2b	SN ← AR	−0.078	0.064	−1.226	**0.220**	Not supported
3a	PB ← CR	0.427	0.050	8.572	***	Supported
3b	PB ← AR	0.025	0.057	0.442	**0.659**	Not supported
4a	BI ← CR	0.096	0.044	2.193	0.028	Supported
4b	BI ← AR	−0.055	0.038	−1.457	**0.145**	Not supported
5	BI ← AT	0.164	0.040	4.058	***	Supported
6	BI ← SN	0.147	0.028	5.300	***	Supported
7	BI ←PB	0.259	0.032	8.136	***	Supported
8	BH ← BI	0.522	0.062	8.391	***	Supported

Note: The bold values denote the *p*-values associated with unsupported hypotheses, specifically those with *p*-values exceeding 0.05.

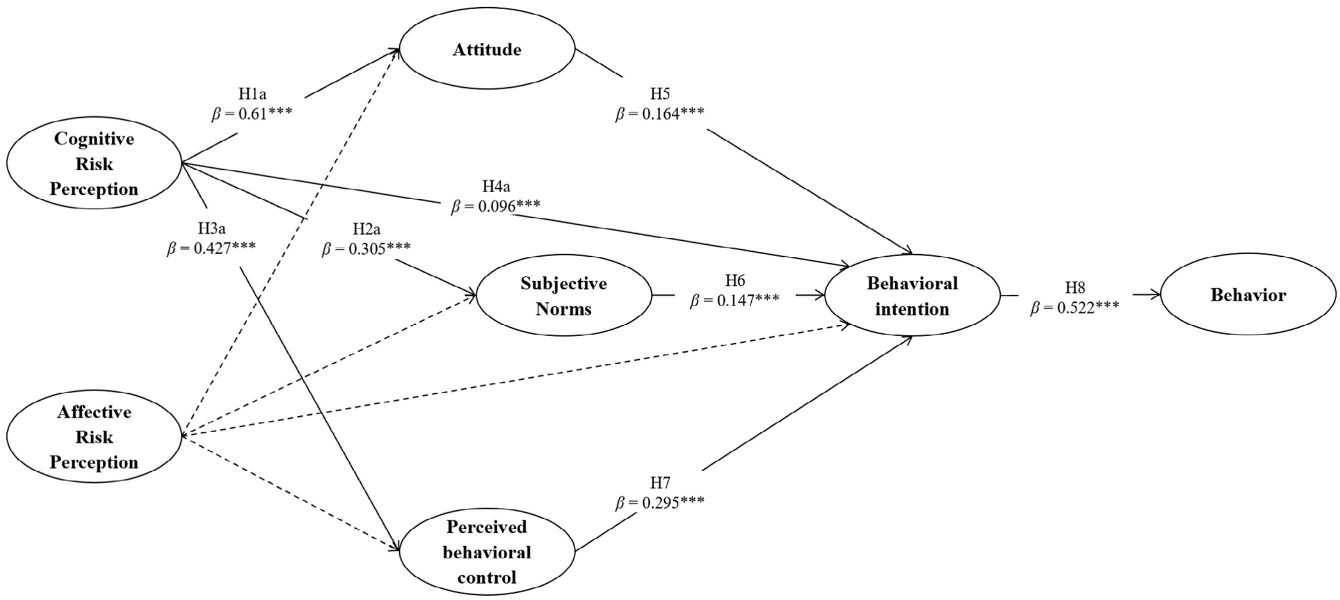

FIGURE 2 | Research model with path relationship among variables.

competence of those participating's perception of untact tourism. In other words, individuals' confidence in their ability to travel safely, along with social influences and personal evaluations, play crucial roles in shaping travel intentions during global crises. These studies underscore the importance of understanding the psychological determinants that drive consumer adoption of contactless services, especially in the evolving landscape of tourism (Liu and Park 2024; Liu et al. 2024). In our study, PB has the strongest influence, followed by AT and SN. However, a study by Boguszewicz-Kreft et al. (2020) examined intentions to participate in medical tourism across three countries and found that AT was the most significant predictor. Another research by Qiu et al. (2022) extends the TPB to predict tourists' pro-environmental intentions and indicates that SN has the most substantial impact. Collectively, these findings highlight the dynamic applicability of the TPB framework in understanding travel behaviors when the global crisis happens.

Finally, our analysis points out that AT, SN, and PB all play a mediating role between CR and BI, and these results align with studies of Agapito et al. (2013), Bae and Chang (2021), and Park et al. (2017). That is, individuals who estimated a higher cognitive risk had more positive AT, SN, and PB regarding untact tourism, and consequently higher BI. This further posits that these factors serve as crucial psychological mechanisms influencing individuals' decision-making processes (Ajzen 1991). The mediating role of AT suggests that CR drives BI more strongly when it is filtered through individuals' cognitive assessments of untact tourism. Shin and Kang (2020) also supposed that perceived safety and convenience

TABLE 8 | Results of qualitative analysis.

Code system	Company A	Compnay B	Company C	Company D	Company E
Response to COVID-19 pandemic					
Saving				■	
Apply for government aid	■	■			
Cut down staff and/or use short-term employees	■			■	
Adjust business effort distribution		■			
Digitalization—Online meeting		■	■		■
Digitalization—Online marketing			■	■	
Digitalization—Online sale					■
Customer Relationship Management			■		
Specific strategy					
Focus on short-term goals	■			■	
Online marketing		■			
Digitalization	■	■			
Customer's research for a recovery strategy					■
Promotions and discounts for customers	■	■	■		
Comply with the government's regulation			■		
New products/services' performance					
Not effective initially	■	■			■
Customers' satisfaction	■		■	■	
Positive impact to company's growth		■	■	■	■
Opinion from customers			■		■
New products/services					
Menu adjustment					■
Self-services (untact service)		■			
Online services	■				■
Automation			■		
Strategy's weakness					
Low profit				■	
Lost of sale		■			
Reputation is easily impacted by fake products					■
Limited budget	■	■	■		
Strategy's strengths					
Saving				■	
Easier operations				■	

(Continues)

TABLE 8 | (Continued)

Code system	Company A	Compnay B	Company C	Company D	Company E
Differentiation		■			
Approach more customers					■
Diversified products					■
High revenue and/or save costs	■				■
Brand's equity and customers relationship			■		
Recommendation					
Active and flexible management				■	
Strategy evaluation	■				
Risk management					■
Innovations and Creativity		■	■		
Online business and digitalization	■	■	■		
Comply government's regulation			■		

can significantly influence consumer adoption of technology-mediated services after a global crisis. Furthermore, the relationship between CR and BI formation is immediately driven by SN as consumers' reliance on social validation—whether from peers, family, or digital sources—was heightened by the crisis when engaging in travel-related activities (Fuchs et al. 2024), leading to an effect on tourism choices, particularly in response to health risks (Williams et al. 2022). Additionally, the mediating role of PB highlights the importance of perceived accessibility and self-efficacy in adopting BI in digital service adoption (Ribeiro et al. 2022). If individuals perceive untact tourism as having too complex technology or being unaffordable, their BI weakens despite a favorable attitude or strong social influence (Cheng et al. 2023).

5.2 | Theoretical Contribution

Our study has several theoretical contributions. First, we provide substantial theoretical implications by developing a comprehensive framework and validated measurement scales for assessing perceived risks and their impact on both behavioral intention and actual behavior in the context of untact tourism. By extending the Theory of Planned Behavior (TPB) to incorporate cognitive and affective risk perceptions, this research enhances understanding of how consumers navigate uncertainty in a global crisis. Unlike traditional TPB applications that focus primarily on intention, this study reinforces the direct link between intention and behavior, offering a more holistic perspective on consumer decision-making. Furthermore, by introducing validated scales specifically designed for the untact tourism context, this study addresses a significant gap in the measurement literature, providing future researchers with robust and replicable instruments that can be applied across different cultural and crisis settings. The integration of both cognitive and affective dimensions into a single unified framework also represents a meaningful theoretical advancement, as it acknowledges that consumer decision-making is driven not only by rational evaluation but also by emotional responses (García-Milon et al. 2020; Godovykh and Tasci 2022), particularly in high-uncertainty environments such as those created by global pandemics.

Second, this study highlights the evolving nature of risk perception throughout different phases of crisis disruption, demonstrating that cognitive and affective risks exert distinct influences on decision-making at various stages. This contributes to a more dynamic understanding of consumer behavior under uncertainty, further confirming that risk perception is not static but fluctuates over time in response to changing situational conditions. In this regard, the findings challenge the conventional assumption embedded in many behavioral models that treat risk perception as a fixed construct (Fuchs et al. 2023; Liu-Lastres et al. 2024) and instead call for a more temporally sensitive theoretical approach. By capturing tourists' perceptions specifically during the late-crisis stage, this study reveals how the gradual easing of pandemic restrictions shapes a distinctive psychological landscape in which both lingering fear and renewed travel optimism coexist. This nuanced insight contributes to a broader theoretical conversation about how consumers recalibrate their risk evaluations as crises evolve, offering scholars a more granular and temporally grounded framework for understanding behavioral change under prolonged disruption. Moreover, the distinction between cognitive and affective risk pathways identified in this study provides a conceptual foundation for future research examining how different types of risk stimuli activate different psychological mechanisms in tourism consumption contexts.

Third, by investigating the Vietnamese tourism industry in the late-crisis stage, this study expands the literature on sustainable tourism, positioning untact tourism as a long-term adaptive strategy in anticipation of future crises. As predicted, there would be an increasing frequency of global disruptions (Trisos et al. 2020), further highlighting the necessity for businesses and policymakers to invest in digital tourism solutions that minimize physical contact while maintaining service quality. In this context, *untact tourism* is not merely a reactive response to the COVID-19 pandemic but rather a proactive and sustainable model that aligns with broader trends in digital transformation and responsible tourism development. By situating the study within the Vietnamese context, this research also contributes to the growing body of literature on tourism behavior in emerging economies, where digital infrastructure and consumer readiness for technology-mediated services may differ significantly from Western contexts (Nguyen et al. 2023). This geographical contribution is particularly valuable as it challenges the tendency in tourism research to generalize findings from developing markets and underscores the importance of context-specific theoretical frameworks. Furthermore, the findings reinforce the argument that sustainable tourism recovery requires not only environmental considerations but also technological resilience (Wang and Petrick 2025), encouraging scholars to broaden the conceptual boundaries of sustainability in tourism to encompass digital and crisis-adaptive dimensions (Rodrigues et al. 2023).

Ultimately, the methodological approach, combining an experimental framework with in-depth interviews with managers in tourism, offers a dual perspective that enhances both theoretical and practical insights and provides a foundation for future studies on risk perception and behavior with tourism models.

5.3 | Practical Contribution

Besides theoretical implications, this study also has practical insights into the tourism industry. In a global crisis, products or services that meet people's demands of limiting perceived dangers can represent a paradigm shift, influencing their intention and behavior in traveling. Remarkably, these products and services can deliver a high degree of personalization rather than short-term alternatives. The higher the cognitive risk perception of individuals, the more likely they are to engage in this type of tourism for their safety. Practically, tourism operators should invest in understanding the psychological profile of their target customers, particularly distinguishing between those driven by cognitive risk concerns and those influenced by affective responses such as fear or anxiety. Tailoring service offerings to address both dimensions, for instance, through transparent health and safety communications alongside emotionally reassuring brand messaging, can significantly enhance customer confidence and drive post-crisis recovery. By aligning service design with the dual nature of risk perception, businesses can position untact tourism not merely as a crisis response, but as a competitive differentiator that builds long-term customer loyalty.

Furthermore, there are a variety of recommendations related to agile management, innovation, and digitalization. First, managers need to consider the importance of contingency plans to allow for more active and flexible management. Risk management and planning are also essential to minimize potential losses. Accordingly, destination management organizations and hospitality operators should establish cross-functional crisis response teams capable of rapidly adapting service delivery models when disruptions occur. Proactive investment in scenario planning, including simulations of future pandemic-like events, can enable tourism businesses to respond with greater speed and strategic clarity rather than reactively improvising under pressure. Second, innovation will be essential in day-to-day business operations, especially in times of volatile markets. Understanding that customers might be confined for a long time and intend to experience tourist activities with high demand but with a different set of expectations from before, tourism suppliers may not only reopen their operations with existing products and services but also bring creative applications to attract customers and meet their satisfaction. This calls for a culture of continuous innovation within tourism organizations, where frontline staff are empowered to identify shifting consumer needs and co-create solutions that bridge the gap between safety requirements and authentic travel experiences. Collaborations between tourism businesses, technology providers, and academic institutions can further accelerate the development of innovative, risk-adaptive service models. Finally, along with rapid technological development, digitalization could substantially contribute to business operations in tourism. Although human interaction has been a noticeable characteristic of tourism, there are many forms of digitalization that could be involved, such as integrating virtual reality technology for tours. Especially in the era of Artificial Intelligence (AI), initiatives like virtual assistants or robotics should be considered for tourist activities to provide more options for customers, even in a global crisis, as well as a means of enhancing their experiences.

5.4 | Limitations and Further Research

Despite its numerous contributions, this research still has limitations. First, the theoretical framework we selected is only one among many that could be applied. There may be other theoretical models that explore the relationship between risk perception and psychological-behavioral variables. We adopted the TPB for its ability to unpack human decision-making into several well-defined components. Moreover, the TPB was already investigated in previous studies on risk perception in tourism (Bae and Chang 2021), so it was natural for us to attempt to further validate previous findings and integrate them with further insights on behavior—a component that was not considered in previous research. In the future, scholars could examine these relationships with other decision-making models such as the Protection Motivation Theory (PMT) or the Health Belief Model (HBM), which emphasize risk perception in the context of self-protection and health-related behaviors. Also, further studies should incorporate more moderator and control variables beyond risk perception, like trust in technology, prior experience with digital services, or individual differences in risk tolerance, to further refine the understanding of untact tourism adoption.

Another limitation arose from our research questions. The sample for the quantitative analysis included experienced users of online services. In this sense, the sample is not necessarily representative of populations with less familiarity with such services. We think, however, that the research question in this study requires people to have a sufficient degree of digital literacy, namely, the ability to effectively navigate the digital world. Future studies therefore could enhance the targeted participants to non-experienced people with online services and conduct comparative analysis to examine the differences among these two groups. A third future research direction could focus on the long-term sustainability of untact tourism by exploring whether consumers will continue using these services once the perceived risk subsides. Future research could adopt a longitudinal approach to track changes in customer preferences over time and determine whether untact tourism becomes a permanent feature of the tourism industry or if traditional in-person services regain dominance.

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Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

Agapito, D., P. Oom do Valle, and J. Da Costa Mendes. 2013. "The Cognitive-Affective-Conative Model of Destination Image: A Confirmatory Analysis." *Journal of Travel & Tourism Marketing* 30, no. 5: 471–481. https://doi.org/10.1080/10548408.2013.803393?journalCode=wttm20.

Ajzen, I. 1991. "The Theory of Planned Behavior." *Organizational Behavior and Human Decision Processes* 50, no. 2: 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Ajzen, I. 2011. "The Theory of Planned Behaviour: Reactions and Reflections." *Psychology & Health* 26, no. 9: 1113–1127. https://doi.org/10.1080/08870446.2011.613995.

Bae, S. Y., and P. Chang. 2021. "The Effect of Coronavirus Disease-19 (COVID-19) Risk Perception on Behavioural Intention Towards 'Untact' Tourism in South Korea During the First Wave of the Pandemic (March 2020)." *Current Issues in Tourism* 24, no. 7: 1017–1035. https://doi.org/10.1080/13683500.2020.1798895.

Barrett, P. 2007. "Structural Equation Modelling: Adjudging Model Fit." *Personality and Individual Differences* 42, no. 5: 815–824. https://doi.org/10.1016/j.paid.2006.09.018.

Barrett, T., and Y. Feng. 2021. "Evaluation of Food Safety Curriculum Effectiveness: A Longitudinal Study of High-School-Aged Youths' Knowledge Retention, Risk-Perception, and Perceived Behavioral Control." *Food Control* 121: 107587. https://doi.org/10.1016/j.foodcont.2020.107587.

Boguszewicz-Kreft, M., S. Kuczamer-Kłopotowska, A. Kozłowski, A. Ayci, and M. Abuhashesh. 2020. "The Theory of Planned Behaviour in Medical Tourism: International Comparison in the Young Consumer Segment." *International Journal of Environmental Research and Public Health* 17, no. 5: 1626. https://doi.org/10.3390/ijerph17051626.

Bordoloi, S., J. Fitzsimmons, and M. Fitzsimmons. 2018. *Service Management: Operations, Strategy, Information Technology*. McGraw-Hill Education.

Chen, J. L., V. Baláž, G. Li, and A. M. Williams. 2026. "Tourist Decision-Making and Types of Crises: Risk Attitudes, Knowledge, and Destination Preference Persistence." *Journal of Hospitality and Tourism Research* 50, no. 2: 271–287. https://doi.org/10.1177/10963480241310819.

Chen, J., A. Marathe, and M. Marathe. 2010. *Coevolution of Epidemics, Social Networks, and Individual Behavior: A Case Study*. Springer. https://doi.org/10.1007/978-3-642-12079-4_28.

Cheng, X., T. Xue, B. Yang, and B. Ma. 2023. "A Digital Transformation Approach in Hospitality and Tourism Research." *International Journal of Contemporary Hospitality Management* 35, no. 8: 2944–2967. https://doi.org/10.1108/IJCHM-06-2022-0679.

Chien, P. M., M. Sharifpour, B. W. Ritchie, and B. Watson. 2017. "Travelers' Health Risk Perceptions and Protective Behavior: A Psychological Approach." *Journal of Travel Research* 56, no. 6: 744–759. https://doi.org/10.1177/0047287516665479.

Davis, F., R. Bagozzi, and P. Warshaw. 1989. "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models." *Management Science* 35, no. 8: 982–1003. https://doi.org/10.1287/mnsc.35.8.982.

Douglas, M., and A. Wildavsky. 1982. *Risk and Culture: An Essay on the Selection of Technical and Environmental Dangers*. University of California Press.

Dryhurst, S., C. R. Schneider, J. Kerr, et al. 2022. "Risk Perceptions of COVID-19 Around the World." In *COVID-19*, 162–174. Routledge.

Esfandiar, K., and A. Hadinejad. 2025. "A Critical Review of the Theory of Planned Behaviour in Tourism Research." *Current Issues in Tourism* 29, no. 8: 1629–1643. https://doi.org/10.1080/13683500.2025.2522246.

Fabrigar, L. R., and D. T. Wegener. 2012. *Exploratory Factor Analysis*. Oxford University Press.

Fishbein, M., and I. Ajzen. 1977. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Addison-Wesley.

Fishbein, M., and I. Ajzen. 2011. *Predicting and Changing Behavior: The Reasoned Action Approach*. Psychology Press.

Fuchs, G., D. Efrat-Treister, and M. Westphal. 2024. "When, Where, and With Whom During Crisis: The Effect of Risk Perceptions and Psychological Distance on Travel Intentions." *Tourism Management* 100: 104809. https://doi.org/10.1016/j.tourman.2023.104809.

Fuchs, L. S., R. F. Schumacher, and J. Long. 2013. "Improving At-Risk Learners' Understanding of Fractions." *Journal of Educational Psychology* 105, no. 3: 683–700. https://doi.org/10.1037/a0032446.

Fuchs, L. S., P. M. Seethaler, D. Fuchs, and D. Espinas. 2023. "Severe Pandemic Learning Loss and the Promise of Remotely Delivered Intervention in Students with Comorbid Reading and Mathematics Learning Difficulty." *Journal of Learning Disabilities* 56, no. 4: 278–294. https://doi.org/10.1177/00222194231170313.

García-Madurga, M. Á., and A. J. Grilló-Méndez. 2023. "Artificial Intelligence in the Tourism Industry: An Overview of Reviews." *Administrative Sciences* 13, no. 8: 172. https://doi.org/10.3390/admsci13080172.

García-Milon, A., E. Juaneda-Ayensa, C. Olarte-Pascual, and J. Pelegrín-Borondo. 2020. "Towards the Smart Tourism Destination: Key Factors in Information Source Use on the Tourist Shopping Journey." *Tourism Management Perspectives* 36: 100730. https://doi.org/10.1016/j.tmp.2020.100730.

Gebretsadik, D., S. Gebremichael, and M. Belete. 2021. "Knowledge, Attitude and Practice Toward COVID-19 Pandemic Among Population Visiting Dessie Health Center for COVID-19 Screening, Northeast Ethiopia." *Infection and Drug Resistance* 14: 905–915. https://doi.org/10.2147/IDR.S297047.

General Statistics Office of Vietnam. 2021. "Report on the COVID-19 impacts on labour and employment situation in the third quarter of 2021. General Statistics Office of Vietnam." https://www.gso.gov.vn/en/data-and-statistics/2021/10/report-on-the-covid-19-impacts-on-labour-and-employment-situation-in-the-third-quarter-of-2021.

General Statistics Office of Vietnam. 2022. "Report on the post-pandemic recovery of employment and labour market in second quarter of 2022. General Statistics Office of Vietnam." https://www.gso.gov.vn/en/data-and-statistics/2022/07/report-on-the-post-pandemic-recovery-of-employment-and-labour-market-in-second-quarter-of-2022.

Ghaderi, Z., R. Butler, and L. Béal. 2022. "Exploring Home-Based Accommodation Operators' Responses to Covid-19: Implications of Untact Hospitality Adoption." *Tourism Management Perspectives* 43: 100979. https://doi.org/10.1016/j.tmp.2022.100979.

Godovykh, M., and A. D. Tasci. 2022. "Emotions, Feelings, and Moods in Tourism and Hospitality Research: Conceptual and Methodological Differences." *Tourism and Hospitality Research* 22, no. 2: 247–253. https://doi.org/10.1177/14673584211039867.

Groot, J., and L. Steg. 2007. "General Beliefs and the Theory of Planned Behavior: The Role of Environmental Concerns in the TPB." *Journal of Applied Social Psychology* 37, no. 8: 1817–1836. https://doi.org/10.1111/j.1559-1816.2007.00239.x.

Guo, C., X. Lu, S. Huang, Y. Zhao, and D. Zhao. 2024. "Understanding the Post-Pandemic Travel Intentions Among Chinese Residents: Impact of Sociodemographic Factors, COVID Experiences, Travel Planned Behaviours, Health Beliefs, and Resilience." *International Journal of Tourism Research* 26, no. 4: e2752. https://doi.org/10.1002/jtr.2752.

Hagger, M. S., M. W. L. Cheung, I. Ajzen, and K. Hamilton. 2022. "Perceived Behavioral Control Moderating Effects in the Theory of Planned Behavior: A Meta-Analysis." *Health Psychology* 41, no. 2: 155. https://doi.org/10.1037/hea0001153.

Hair, J. F., M. Sarstedt, and T. M. Pieper. 2012. "The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications." *Long Range Planning* 45, no. 5–6: 320–340. https://doi.org/10.1016/j.lrp.2012.09.008.

Han, H., B. Meng, and W. Kim. 2017. "Emerging Bicycle Tourism and the Theory of Planned Behavior." *Journal of Sustainable Tourism* 25, no. 2: 292–309. https://doi.org/10.1080/09669582.2016.1202955.

Hoe, S. L. 2008. "Issues and Procedures in Adopting Structural Equation Modelling Technique." *Journal of Quantitative Methods* 3, no. 1: 76. https://ink.library.smu.edu.sg/sis_research/5168.

Hu, L., and P. M. Bentler. 1999. "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives." *Structural Equation Modeling: A Multidisciplinary Journal* 6, no. 1: 1–55. https://doi.org/10.1080/10705519909540118.

Hua, C., S. Cole, Y. Zhang, W. Wang, and H. Zhao. 2025. "Exploring Needed Support as a Motivational Factor for Travelers With Mobility Impairments: A Sequential Mixed-Methods Exploration." *Journal of Travel Research* 64, no. 2: 378–394. https://doi.org/10.1177/00472875231215017.

Huang, L., C. Chiang, and H. Chen. 2014. "Willingness to Pay of Visitors for the Nature-Based Public Park: An Extension of Theory of Planning Behavior (TPB)." *Journal of Information and Optimization Sciences* 35, no. 5–6: 405–429. https://doi.org/10.1080/02522667.2014.903701.

Huang, X., S. Dai, and H. Xu. 2020. "Predicting Tourists' Health Risk Preventative Behaviour and Travelling Satisfaction in Tibet: Combining the Theory of Planned Behaviour and Health Belief Model." *Tourism Management Perspectives* 33: 100589. https://doi.org/10.1016/j.tmp.2019.100589.

Huang, X., X. R. Li, and L. Lu. 2023. "Travel Shaming? Re-Thinking Travel Decision Making Amid a Global Pandemic." *Tourism Management* 94: 104658. https://doi.org/10.1016/j.tourman.2022.104658.

Hüsser, A. P., T. Ohnmacht, and V. T. Thao. 2024. "Tourists' Preventive Travel Behaviour During COVID-19: The Mediating Role of Attitudes Towards Applying Non-Pharmaceutical Interventions (NPIs) While Travelling." *Current Issues in Tourism* 27, no. 1: 127–141. https://doi.org/10.1080/13683500.2022.2162373.

International Trade Administration. 2021. *Vietnam Digital Economy and Regulatory Challenges*. International Trade Administration. https://www.trade.gov/market-intelligence/vietnam-digital-economy-and-regulatory-challenges.

Jeong, J. Y., J. L. Crompton, and K. Y. Lee. 2022. "Applying the TRIRISK Model to COVID-19 in Tourism: A Comparison Between 2020 and 2021." *Tourism Management Perspectives* 41: 100936. https://doi.org/10.1016/j.tmp.2022.100936.

Kline, R. B. 2016. *Principles and Practice of Structural Equation Modeling*. Fourth ed. Guilford Publications.

Lai, F., C. Xie, Y. Chen, and R. Huang. 2025. "Humor or Fear: Which Tourism Warning Message Appeals Are More Persuasive." *Journal of Travel Research*: 00472875251361906. https://doi.org/10.1177/00472875251361906.

Lee, S. M., and D. Lee. 2020. ""Untact": A New Customer Service Strategy in the Digital Age." *Service Business* 14, no. 1: 1–22. https://doi.org/10.1007/s11628-019-00408-2.

Li, S., M. Chen, X. Ma, and Z. Sun. 2024. "Applying an Extended Protection Motivation Theory Model to Predict Resident Hospitality During the COVID-19 Crisis." *Journal of Travel Research* 63, no. 5: 1201–1218. https://doi.org/10.1177/00472875231187334.

Liu, H., and K. S. Park. 2024. "Exploring the Impact of Metaverse Tourism Experiences on Actual Visit Intentions: An Integrated Model of Presence, the Technology Acceptance Model, and the Theory of Planned Behavior." *International Journal of Tourism Research* 26, no. 1: e2616. https://doi.org/10.1002/jtr.2616.

Liu, J. Q., C. Y. Jeon, and H. W. Yang. 2024. "What Drives Tourists to Take a Digital-Free Tourism?" *International Journal of Tourism Research* 26, no. 4: e2674. https://doi.org/10.1002/jtr.2674.

Liu-Lastres, B., Y. Yang, and C. X. Zhang. 2024. "Optimal-Fit Model of Risk Perception and Travel-Related Behaviors During a Global Pandemic." *Journal of Destination Marketing & Management* 34: 100958. https://doi.org/10.1016/j.jdmm.2024.100958.

Lobb, A. E., M. Mazzocchi, and W. B. Traill. 2007. "Modelling Risk Perception and Trust in Food Safety Information Within the Theory of Planned Behaviour." *Food Quality and Preference* 18, no. 2: 384–395. https://doi.org/10.1016/j.foodqual.2006.04.004.

Loewenstein, G. F., E. U. Weber, C. K. Hsee, and N. Welch. 2001. "Risk as feelings." *Psychological Bulletin* 127, no. 2: 267–286. https://psycnet.apa.org/buy/2001-16969-005.

Long, N. N., and B. H. Khoi. 2020. "An Empirical Study About the Intention to Hoard Food During COVID-19 Pandemic." *Eurasia Journal of Mathematics, Science and Technology Education* 16, no. 7: em1857. https://doi.org/10.29333/ejmste/8207.

Manstead, A. S. R. 2001. "Attitudes and Behaviour." *International Encyclopedia of the Social & Behavioral Sciences*, edited by N. J. Smelser, and P. B. Baltes, 909–913. https://doi.org/10.1016/B0-08-043076-7/01759-9.

Marsh, H. W., A. J. Morin, P. D. Parker, and G. Kaur. 2014. "Exploratory Structural Equation Modeling: An Integration of the Best Features of Exploratory and Confirmatory Factor Analysis." *Annual Review of Clinical Psychology* 10: 85–110. https://doi.org/10.1146/annurev-clinpsy-032813-153700.

Maruyama, G. 1997. *Basics of Structural Equation Modeling*. Sage.

Miao, L., J. Im, K. K. F. So, and Y. Cao. 2022. "Post-Pandemic and Post-Traumatic Tourism Behavior." *Annals of Tourism Research* 95: 103410. https://doi.org/10.1016/j.annals.2022.103410.

Mogaji, E., I. Adekunle, S. Aririguzoh, and A. Oginni. 2022. "Dealing With Impact of COVID-19 on Transportation in a Developing Country:

Insights and Policy Recommendations." *Transport Policy* 116: 304–314. https://doi.org/10.1016/j.tranpol.2021.12.002.

Nastasi, B. K., J. H. Hitchcock, and L. M. Brown. 2010. "An Inclusive Framework for Conceptualizing Mixed Methods Design Typologies: Moving Toward Fully Integrated Synergistic Research Models." In *SAGE Handbook of Mixed Methods in Social & Behavioral Research*, 305–338. SAGE Publications, Inc.

Nguyen-Anh, T., S. Leu, A. Nguyen-Thi-Phuong, T. Ngo-Dang, and To-The, N. 2023. "Adapting to the New Normal: A Sustainable Livelihood Framework for the Informal Sectors During COVID-19." *Review of Development Economics* 27, no. 2: 1092–1112. https://doi.org/10.1111/rode.12974.

O'Neal, P. W. 2007. *Motivation of Health Behavior*. Nova Science Pubs.

Pappas, N., A. Caputo, M. M. Pellegrini, G. Marzi, and E. Michopoulou. 2021. "The Complexity of Decision-Making Processes and IoT Adoption in Accommodation SMEs." *Journal of Business Research* 131: 573–583. https://doi.org/10.1016/j.jbusres.2021.01.010.

Park, S., C. Hsieh, and C. Lee. 2017. "Examining Chinese College Students' Intention to Travel to Japan Using the Extended Theory of Planned Behavior: Testing Destination Image and the Mediating Role of Travel Constraints." *Journal of Travel & Tourism Marketing* 34, no. 1: 113–131. https://doi.org/10.1080/10548408.2016.1141154.

Pyszczynski, T., M. Lockett, J. Greenberg, and S. Solomon. 2021. "Terror Management Theory and the COVID-19 Pandemic." *Journal of Humanistic Psychology* 61, no. 2: 173–189. https://doi.org/10.1177/0022167820959488.

Qiu, H., X. Wang, A. M. Morrison, C. Kelly, and W. Wei. 2022. "From Ownership to Responsibility: Extending the Theory of Planned Behavior to Predict Tourist Environmentally Responsible Behavioral Intentions." *Journal of Sustainable Tourism* 33, no. 6: 1122–1145. https://doi.org/10.1080/09669582.2022.2116643.

Rädiker, S., and U. Kuckartz. 2020. *Focused Analysis of Qualitative Interviews With MAXQDA*. MAXQDA Press.

Reisinger, Y., and F. Mavondo. 2005. "Travel Anxiety and Intentions to Travel Internationally: Implications of Travel Risk Perception." *Journal of Travel Research* 43, no. 3: 212–225. https://doi.org/10.1177/0047287504272017.

Ribeiro, M. A., D. Gursoy, and O. H. Chi. 2022. "Customer Acceptance of Autonomous Vehicles in Travel and Tourism." *Journal of Travel Research* 61, no. 3: 620–636. https://doi.org/10.1177/0047287521993578.

Rodrigues, V., C. Eusébio, and Z. Breda. 2023. "Enhancing Sustainable Development Through Tourism Digitalisation: A Systematic Literature Review." *Information Technology & Tourism* 25, no. 1: 13–45. https://doi.org/10.1007/s40558-022-00241-w.

Rozenkowska, K. 2023. "Theory of Planned Behavior in Consumer Behavior Research: A Systematic Literature Review." *International Journal of Consumer Studies* 47, no. 6: 2670–2700. https://doi.org/10.1111/ijcs.12970.

Schmiege, S. J., A. Bryan, and W. M. Klein. 2009. "Distinctions Between Worry and Perceived Risk in the Context of the Theory of Planned Behavior." *Journal of Applied Social Psychology* 39, no. 1: 95–119. https://doi.org/10.1111/j.1559-1816.2008.00431.x.

Sheeran, P., P. R. Harris, and T. Epton. 2014. "Does Heightening Risk Appraisals Change People's Intentions and Behavior? A Meta-Analysis of Experimental Studies." *Psychological Bulletin* 140, no. 2: 511–543. https://doi.org/10.1037/a0033065.

Shin, H., and J. Kang. 2020. "Reducing Perceived Health Risk to Attract Hotel Customers in the COVID-19 Pandemic Era: Focused on Technology Innovation for Social Distancing and Cleanliness." *International Journal of Hospitality Management* 91: 102664. https://doi.org/10.1016/j.ijhm.2020.102664.

Slovic, P. 2000. "What Does It Mean to Know a Cumulative Risk? Adolescents' Perceptions of Short-Term and Long-Term Consequences of Smoking." *Journal of Behavioral Decision Making* 13, no. 2: 259–266. https://doi.org/10.1002/(SICI)1099-0771(200004/06)13:2%3C259::AID-BDM336%3E3.0.CO;2-6.

Slovic, P., M. L. Finucane, E. Peters, and D. G. MacGregor. 2004. "Risk as Analysis and Risk as Feelings: Some Thoughts About Affect, Reason, Risk and Rationality." *Risk Analysis: An International Journal* 24, no. 2: 311–322. https://doi.org/10.1111/j.0272-4332.2004.00433.x.

Stechemesser, A., M. Kotz, M. Auffhammer, and L. Wenz. 2023. "Prolonged Exposure Weakens Risk Perception and Behavioral Mobility Response: Empirical Evidence From Covid-19." *Transportation Research Interdisciplinary Perspectives* 22: 100906. https://doi.org/10.1016/j.trip.2023.100906.

Sterman, J., and G. Dogan. 2015. "I'm Not Hoarding, I'm Just Stocking Up Before the Hoarders Get Here." *Journal of Operations Management* 39–40, no. 1: 6–22. https://doi.org/10.1016/j.jom.2015.07.002.

Tadese, M., B. A. Haile, T. Moltot, and M. Silesh. 2021. "Perceived Risk of Covid-19 and Related Factors Among University Students in Ethiopia During School Reopening." *Infection and Drug Resistance* 14: 953–961. https://doi.org/10.2147/IDR.S302126.

Thompson, N., and K. Thompson. 1996. "Reasoned Action Theory: An Application to Alcohol-Free Beer." *Journal of Marketing Practice: Applied Marketing Science* 2, no. 2: 35–48. https://doi.org/10.1108/EUM0000000000020.

Trisos, C. H., C. Merow, and A. L. Pigot. 2020. "The Projected Timing of Abrupt Ecological Disruption From Climate Change." *Nature* 580, no. 7804: 496–501. https://doi.org/10.1038/s41586-020-2189-9.

Ulker-Demirel, E., and G. Ciftci. 2020. "A Systematic Literature Review of the Theory of Planned Behavior in Tourism, Leisure and Hospitality Management Research." *Journal of Hospitality and Tourism Management* 43: 209–219. https://doi.org/10.1016/j.jhtm.2020.04.003.

Van, N. T. T., V. Vrana, N. T. Duy, et al. 2020. "The Role of Human–Machine Interactive Devices for Post-COVID-19 Innovative Sustainable Tourism in Ho Chi Minh City, Vietnam." *Sustainability* 12, no. 22: 9523. https://doi.org/10.3390/su12229523.

Villacé-Molinero, T., J. J. Fernández-Muñoz, A. Orea-Giner, and L. Fuentes-Moraleda. 2021. "Understanding the New Post-COVID-19 Risk Scenario: Outlooks and Challenges for a New Era of Tourism." *Tourism Management* 86: 104324. https://doi.org/10.1016/j.tourman.2021.104324.

Wang, X., and J. F. Petrick. 2025. "Understanding Traveler Behavior Before, During, and Post COVID-19." *International Journal of Tourism Research* 27, no. 5: e70137. https://doi.org/10.1002/jtr.70137.

Williams, A. M., J. L. Chen, G. Li, and V. Baláž. 2022. "Risk, Uncertainty and Ambiguity Amid COVID-19: A Multi-National Analysis of International Travel Intentions." *Annals of Tourism Research* 92: 103346. https://doi.org/10.1016/j.annals.2021.103346.

Wong, L., H. Alias, and P. Wong. 2020. "The Use of the Health Belief Model to Assess Predictors of Intent to Receive the COVID-19 Vaccine and Willingness to Pay." *Human Vaccines & Immunotherapeutics* 16, no. 9: 2204–2214. https://doi.org/10.1080/21645515.2020.1790279.

World Bank. 2023. *Country Case Study*. World Bank. https://thedocs.worldbank.org/en/doc/8ca3f9bfda06e5c061ef3affd92fb551-0070012023/original/Vietnam-case-study.pdf.

Wu, J., and H. Du. 2012. "Toward a Better Understanding of Behavioral Intention and System Usage Constructs." *European Journal of Information Systems* 21, no. 6: 680–698. https://doi.org/10.1057/ejis.2012.15.

Wu, J. S., X. Font, and J. Liu. 2021. "The Elusive Impact of Pro-Environmental Intention on Holiday on Pro-Environmental Behaviour at Home." *Tourism Management* 85: 104283. https://doi.org/10.1016/j.tourman.2021.104283.

Yang, Y., C. X. Zhang, and J. M. Rickly. 2021. "A Review of Early COVID-19 Research in Tourism: Launching the Annals of Tourism Research's Curated Collection on Coronavirus and Tourism." *Annals of Tourism Research* 91: 103313. https://doi.org/10.1016/j.annals.2021.103313.

Yang, Y., H. Zhang, and X. Chen. 2020. "Coronavirus Pandemic and Tourism: Dynamic Stochastic General Equilibrium Modeling of Infectious Disease Outbreak." *Annals of Tourism Research* 83: 102913. https://doi.org/10.1016/j.annals.2020.102913.

Yin, X., H. Liu, Y. Chen, and M. Al-Hussein. 2019. "Building Information Modelling for Off-Site Construction: Review and Future Directions." *Automation in Construction* 101: 72–91. https://doi.org/10.1016/j.autcon.2019.01.010.

Zheng, D., Q. Luo, and B. W. Ritchie. 2021. "Afraid to Travel After COVID-19? Self-Protection, Coping and Resilience Against Pandemic 'Travel Fear'." *Tourism Management* 83: 104261. https://doi.org/10.1016/j.tourman.2020.104261.

Zhong, L., S. Sun, R. Law, and X. Qi. 2024. "Tourists' Perception of Health Tourism Before and After COVID-19." *International Journal of Tourism Research* 26, no. 1: e2620. https://doi.org/10.1002/jtr.2620.