

Article

Navigating Health-Related Crises: Unraveling the Role of Confidence in Tourism Recovery in Shaping Sustainable Strategies for Tourists' Intentions across Pandemic Phases

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Abstract: The COVID-19 pandemic has severely impacted global tourism, raising the need for sustainable recovery strategies. This study examines how tourists' confidence in tourism recovery (CTR) influences travel intentions across different pandemic phases—outbreak, stabilization, and conclusion. Positioned within the Theory of Planned Behavior (TPB), the research explores the mediating role of CTR in the relationships between attitude, subjective norms, perceived behavioral control, and travel intention. Using structural equation modeling (SEM), multi-group analysis (MGA), and Importance–Performance Matrix Analysis (IPMA), this study assesses changes in travel behavior during each pandemic phase. Data were collected through three surveys conducted in major Chinese cities between late 2022 and early 2023. The findings reveal that CTR significantly mediates the influence of behavioral factors on travel intention, especially during the stabilization and conclusion phases. The IPMA results highlight key areas for intervention, with CTR, perceived behavioral control, and subjective norms varying in importance across phases. This research underscores the need for adaptive and sustainable strategies to strengthen traveler confidence, offering practical insights for supporting long-term resilience and growth in the tourism industry during and beyond health-related crises.

Keywords: confidence in tourism recovery (CTR); health-related crisis management; sustainable recovery; Partial Least Squares (PLS); Importance–Performance Matrix Analysis (IPMA)



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1. Introduction

The global tourism industry, a significant driver of economic growth and cultural exchange, is uniquely sensitive to health-related crises. Among these, the COVID-19 pandemic has posed an unprecedented challenge worldwide. Over the past three years, significant fluctuations in tourist arrivals have been observed as the pandemic evolved [1]. Despite evident signs of recovery in 2023 and 2024, the resurgence of health-related crises continues to threaten tourism stability, underscoring the importance of understanding how tourist confidence drives sustainable recovery strategies [2–5].

Existing research on tourism behavior during crises has predominantly focused on risk perception, media influence, and health awareness, often centered on the early stages of the pandemic [6–18]. These studies have provided valuable insights into how fear and uncertainty shape travel intentions. However, much of the literature remains limited by its reliance on cross-sectional data and static analyses, neglecting the dynamic evolution of tourists' behavior across different pandemic phases. This gap in longitudinal analysis hinders our understanding of how confidence in tourism recovery (CTR) dynamically influences travel intentions during health-related crises.

To bridge this gap, this study introduces CTR as a key mediating variable within the framework of the Theory of Planned Behavior (TPB). While TPB has proven robust in predicting behavioral intentions across various contexts, its application in pandemic scenarios remains under-explored. By integrating CTR, this study aims to enhance the predictive power of TPB in the context of tourism recovery, offering a more comprehensive understanding of how attitudes, subjective norms, and perceived behavioral control interact with CTR to shape travel intentions.

In addition, by drawing on longitudinal data collected from three rounds of surveys conducted in major Chinese cities between late 2022 and early 2023, the research captures real-world shifts in tourists' behavior as the pandemic progressed. To enable dynamic tracking of behavioral shifts and identification of key areas for improving sustainable tourism strategies, this study utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM), combined with Multi-Group Analysis (MGA) and Importance–Performance Matrix Analysis (IPMA) to explore the mediating role of confidence in tourism recovery (CTR) across different pandemic phases. The findings underscore the importance of adaptive strategies that strengthen tourists' confidence and support sustainable tourism recovery, particularly in response to ongoing health-related uncertainties [4,5].

By addressing these issues, this research contributes to the growing body of literature on crisis management in tourism and provides actionable insights for both policymakers and industry stakeholders to design adaptive strategies that build tourists' confidence and support long-term resilience in the face of health-related uncertainties.

2. Literature Review

2.1. Tourists' Behavioral Intention

Behavioral intention refers to an individual's readiness or plan to perform a specific action [19,20] and has been a focal point in fields such as behavioral science, psychology, and management for predicting actual behavior [21–25]. In tourism, behavioral intention involves decisions related to traveling [26], revisiting destinations [24,27], participating in activities [28], or recommending locations to others [29,30]. As behavioral intention offers insights into how tourists make decisions, researchers and practitioners are keen to explore the factors influencing these intentions. Recent reviews, such as that by Seyfi et al. (2024), identified multiple influencing factors, including risk perception, trust, past experiences, and media coverage [6].

Researchers consistently emphasize the dual role of travel inhibitors and motivators in shaping behavioral intentions [26,30,31]. During health-related crises such as COVID-19, tourists' intentions become particularly complex and are subject to significant changes. Early pandemic research primarily focused on inhibitors, such as health risks, anxiety, and travel restrictions [7–10,32]. However, as the pandemic subsides, attention is shifting towards motivators such as satisfaction, trust, and positive experiences [26,31], which are expected to play a stronger role in driving travel intentions post-crisis. For instance, Fuchs et al. (2024) suggest that strong motivators can outweigh risk concerns [10], while Kim et al. (2022) highlight that anticipated positive emotional experiences significantly boost travel likelihood in the post-pandemic period [12].

2.2. Theory of Planned Behavior

Rooted in the theory of reasoned action, the Theory of Planned Behavior (TPB) is a widely applied framework for predicting behavioral intentions by examining attitudes, subjective norms, and perceived behavioral control [20,33]. In tourism research, TPB has consistently demonstrated its robustness in understanding travel intentions, especially during and after the pandemic [29,30,33–36]. Beyond its established predictive power, the adaptability of TPB allows for the inclusion of additional variables, enhancing its relevance in varying contexts [37]. For instance, Yuzhanin and Fisher (2016) suggested extending TPB by adding new constructs to better account for the unique factors influencing tourist behavior, particularly in crisis situations [38].

Recent studies have integrated TPB with other frameworks to explore shifts in travel intentions during crises. For example, Hüsser et al. (2023) combined TPB with the Health Belief Model (HBM) to analyze how perceived health risks influence travel decisions during COVID-19 [13]. Additionally, the Stimulus–Organism–Response (S-O-R) model and the Protection Motivation Theory (PMT) have been introduced to extend TPB in research to address factors such as perceived risk, information overload, and fear [7,39]. Other extensions have incorporated constructs such as perceived risk [8,10,14], emotional responses [10], and trust [7,40,41] to capture factors not covered by the original TPB framework.

Although TPB remains central in predicting travel intentions, there is a growing need for longitudinal research to track the changes in tourist behavior intentions as the pandemic evolves and recovery progresses. As Yuzhanin and Fisher (2016) suggest, such studies can offer deeper insights into how intentions and behaviors change over time [38], which may guide the tourism industry in adapting to tourists' shifting preferences and maintaining sustainability.

2.3. Tourists' Confidence in Tourism Recovery

Consumer confidence is a well-established indicator in marketing and economics. High consumer confidence typically leads to increased spending and economic growth, while low confidence results in reduced consumption and economic stagnation [15,42,43]. In tourism research, this concept parallels tourists' confidence, which plays a vital role in shaping travel decisions. Just as consumers' confidence influences their spending, tourists' confidence directly affects their perceptions of safety and attractiveness of a destination, which becomes a decisive factor in the recovery of destination image and tourists' behavior, impacting whether or not they choose to visit a destination post-crisis [44,45].

Based on the previous studies, this research extends the concept of consumer confidence to the specific context of post-pandemic tourism recovery. Tourists' confidence in tourism recovery (CTR) is defined as the collective assurance and positive expectations tourists hold regarding the tourism sector's ability to rebound from health crises. Dissimilar to the broader consumer confidence, which reflects overall financial stability and economic outlook, CTR is concerned with how tourists perceive the tourism sector's efforts to ensure safety, manage risks, and restore services after a crisis [2]. CTR is thus a more focused construct, offering a detailed view of how tourism-specific recovery efforts influence tourists' decisions.

In pandemic-related studies, tourists' trust has been a primary focus for predicting behavioral intentions [7,40,41]. While trust involves a relational and long-term perspective, CTR addresses the immediate perceptions of recovery and safety. It reflects real-time responses to crisis management, providing a more dynamic measure of how tourists react to recovery efforts [35,46–48]. Therefore, a study of the CTR variable will differ from previous research, allowing us to explore tourism recovery and post-pandemic sustainable development from a more dynamic perspective.

Notably, rebuilding tourists' confidence in the recovery of the tourism industry has been highlighted as a crucial path to economic restoration in some research [49–52]. Dissimilar to previous studies, our research integrates CTR with the Theory of Planned Behavior (TPB), aiming to provide a comprehensive understanding of tourists' behavioral intentions in the context of post-pandemic sustainable recovery of tourism.

2.4. Dynamics of Tourists' Travel Intentions across Different Stages in the Development of a Health-Related Crisis

Health-related crises, such as COVID-19, progress through distinct stages, each bringing unique public health challenges. Understanding these stages is crucial for effective crisis management and for developing strategies to mitigate the impact on tourism [52,53]. Cheer et al. (2021) emphasized the importance of dynamically tracking tourists' behavior across these stages to refine tourism crisis management strategies [54].

However, most existing studies rely on cross-sectional data collected at specific stages of a crisis, limiting their ability to capture the evolution of tourists' travel intentions. For instance, early research focused on initial reactions through text mining techniques [55], while later studies shifted to examine health interventions such as mask-wearing or social distancing during stabilization phases [56–58]. In the post-pandemic stage, research primarily addresses recovery and lasting shifts in tourism behaviors [12,59–62].

This highlights a significant gap in research that continuously tracks tourists' intentions throughout all stages of a crisis. Such continuous analysis offers valuable insights for policymakers and industry stakeholders, enabling timely adaptations to changing conditions [10,52,63]. Casal-Ribeiro et al. (2023) underscore that dynamic tracking allows for real-time adjustments in response to shifting behaviors [63], while other studies advocate for ongoing research to fully understand evolving travel decisions [16,17].

To fill this gap, this study uses longitudinal data collected across multiple pandemic stages to provide dynamic insights into tourists' intentions, addressing a crucial need in the existing literature.

3. Conceptual Model and Hypotheses Development

The current study proposes a conceptual model (see Figure 1) to identify how the travel motivators, such as tourists' confidence in tourism recovery (CTR), integrate with the original TPB framework to tourists' behavioral intentions as the pandemic progresses. Beyond the primary constructs, several control variables were introduced to mitigate the potential confounding effects arising from respondents' characteristics on the outcome variable. These control variables include age, gender, education, and marriage, as outlined in Figure 1. The objective of this section is to discuss each construct and hypothesis related to the causal relationships within the proposed model.

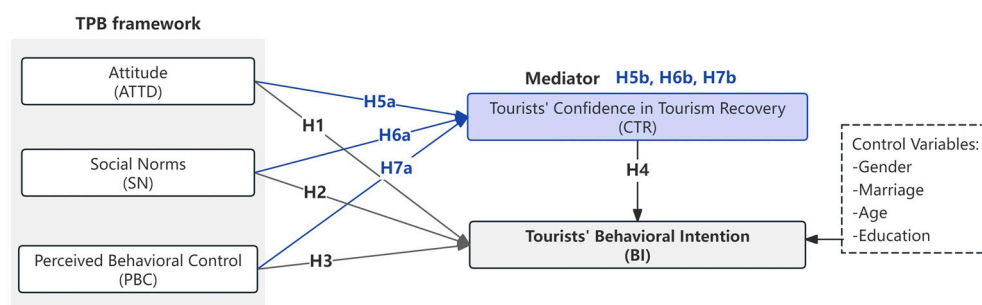


Figure 1. Research Model.

3.1. TPB-Based Constructs and Hypotheses

The Theory of Planned Behavior (TPB) is a widely used framework for predicting a variety of human behaviors, including tourist intentions. It is particularly effective in the context of health-related crises because it provides a structured way to understand the factors, and it is open to the addition of other predictive variables [20,37]. TPB posits that three core components influence behavioral intentions, namely, attitude (hereinafter referred to as ATTD), subjective norms (hereinafter referred to as SN), and perceived behavioral control (hereinafter referred to as PBC) [20,64]. Tourist attitude refers to the individual's positive or negative evaluations of traveling. During a crisis such as the COVID-19 pandemic, the TPB effectively captures this dynamic by linking attitudes directly to behavioral intentions, which were tested by many empirical studies [7,30,65–67]. Subjective norms involve the perceived social pressure to perform or not perform the behavior. In the context of health-related crisis, tourists' travel decisions can be influenced by family, friends, and social media, which was demonstrated in some previous research [7,16,39,68–70]. Perceived behavioral control refers to an individual's perception of resources, opportunities, and abilities to perform a certain behavior. Individuals with high perceived behavioral control always demonstrate a stronger behavioral intention [20]. It is considered to be salient where

travel barriers (e.g., financial constraints, health risks, and accessibility issues) can significantly influence decisions. Tourists are more likely to travel if they feel confident in their ability to overcome these barriers, which have been asserted by some pandemic-related researchers [10,66,70]. Based on the original TPB framework and the previous empirical research, this study proposes the following hypotheses:

H1. *Attitude toward travel positively influences tourists' behavioral intention during and after the pandemic.*

H2. *Social norms positively influence tourists' behavioral intentions during and after the pandemic.*

H3. *Perceived behavioral control positively influences tourists' behavioral intention during and after the pandemic.*

3.2. Incorporating the Construct of Tourists' Confidence in Tourism Recovery (CTR) into the TPB

This study extends the TPB model by adding the construct of Tourists' Confidence in Tourism Recovery (CTR), which is conceptualized as the level of assurance and positive expectation that tourists hold regarding the ability of the tourism sector to effectively rebound and restore its services, safety, infrastructure, and overall travel experience in the aftermath of a health-related crisis.

Both in academic research and practice, the close relationship between consumer confidence and economic behavior has been widely recognized. The UNWTO uses the Tourism Confidence Index to predict tourism demand for destinations. Previous studies emphasize that confidence levels significantly affect tourists' decision-making processes during crises [71–73]. During a health-related crisis, the increased uncertainty amplifies the impact of psychological factors on tourists' travel intentions. The stronger the tourists' confidence in the recovery of the destination, the greater their intention to travel. Based on this, we propose the hypothesis as follows:

H4. *Tourists' confidence in tourism recovery (CTR) positively influences tourists' behavioral intention to travel during and after the pandemic.*

The current study posits that Tourists' Confidence in Tourism Recovery (CTR) plays a crucial mediating role between the three antecedent variables (attitudes, subjective norms, and perceived behavioral control) and the dependent variable of travel intention, which may enhance the predictive power of the TPB framework during and after the pandemic.

First, according to the Attitude–Behavior Relationship Theory, an individual's attitude towards a particular matter influences their beliefs and confidence regarding that matter [19,20]. During a crisis such as the COVID-19 pandemic, when tourists develop favorable attitudes toward travel—believing it to be enjoyable, safe, and valuable—these attitudes bolster their Confidence in Tourism Recovery (CTR). Positive attitudes signal a belief that tourism infrastructure is resilient and that travel will be met with adequate support, such as safety measures and services [20]. Some research suggests that when individuals hold favorable attitudes, they are more likely to trust in the success and recovery of the systems supporting their behavior, in this case, the tourism industry [71].

Without CTR, even a positive attitude may not translate into travel behavior due to lingering doubts or perceived barriers. Therefore, CTR serves as a critical mediator between attitude and actual behavioral intention, enhancing the belief that the behavior (travel) is supported and will be successfully executed [52]. In light of this, the hypotheses can be developed as follows:

H5a. *Attitude (ATTD) towards travel positively influences Tourists' Confidence in Tourism Recovery (CTR) during and after the pandemic.*

H5b. *Tourists' Confidence in Tourism Recovery (CTR) mediates the relationship between tourists' attitudes (ATTD) and their behavioral intention to travel (BI) during and after the pandemic.*

Second, in the context of tourism, social norms encompass the expectations and behaviors of peers, family, media, and society regarding travel. During and after the health-related crisis, social norms play a prominent role in people's decision-making process [74]. When tourists observe that others are confident in the recovery of the tourism industry and are starting to travel again, their own confidence in the industry's recovery is bolstered. The role of social learning theory can also be integrated here, where individuals learn behaviors by observing others, particularly in ambiguous situations such as a post-crisis recovery phase [75].

This increased confidence enhances their intention to travel, aligning their personal attitudes with positive social norms. Recovery confidence serves as a bridge in this process by providing assurance that traveling is not only socially endorsed but also safe [50]. Given the crucial influence of tourists' confidence on the relationship between, particularly in the context of post-crisis recovery, the following hypotheses are proposed:

H6a. *Social norms (SN) positively influence Tourists' Confidence in Tourism Recovery (CTR) during and after the pandemic.*

H6b. *Tourists' Confidence in Tourism Recovery (CTR) mediates the relationship between social norms (SN) and tourists' behavioral intention to travel (BI) during and after the pandemic.*

Third, Perceived behavioral control (PBC) is repeatedly proven to serve as a predictor of a particular intention or behavior [20]. In the context of health-related crises, PBC encompasses tourists' confidence in their ability to travel, considering factors such as financial resources, health and safety, logistical ease, and regulatory requirements. Tourists who feel they can navigate these obstacles—by, for example, adhering to safety protocols, managing finances, or making informed travel choices—are more likely to trust that they can travel safely and successfully. High levels of PBC reflect the optimistic mindsets of tourists, which boosts their positive belief in the tourism sector's ability to rebound and provide safe, enjoyable experiences post-crisis [50].

In this sense, PBC not only reflects tourists' belief in their ability to act but also builds their trust in the recovery of the tourism sector. Therefore, under the unique conditions of the pandemic, high levels of PBC significantly enhance CTR, and this enhanced confidence mediates the relationship between PBC and actual travel intentions. Based on this, the current study proposes the following hypotheses:

H7a. *Perceived behavioral control (PBC) positively influences Tourists' Confidence in Tourism Recovery (CTR) during and after the pandemic.*

H7b. *Tourists' Confidence in Tourism Recovery (CTR) mediates the relationship between Perceived behavioral control (PBC) and tourists' behavioral intention to travel (BI) during and after the pandemic.*

4. Methodology

4.1. Overall Design

This study employs a survey-based approach, a widely used quantitative method to test hypotheses and validate theoretical models [76]. Conducted in the second half of 2022 during the global COVID-19 pandemic, this study utilized a quasi-experimental design with real-world scenarios. We grouped respondents by their perceived stage of epidemic development (PSED) and used PLS-MGA (Partial Least Squares Multi-Group Analysis) to assess differences in model relationships across groups and IPMA (Importance–

Performance Map Analysis) to evaluate the importance and performance of constructs identifying areas for impactful improvements.

4.2. Questionnaire Design and Measure Instrument

A structured questionnaire was designed to capture tourists' psychological responses during the pandemic. The questionnaire was divided into three sections. The first section presented pandemic-related scenarios for respondents to assess which best fit their perception. The second section measured key constructs, including attitude towards travel (ATTD), subjective norms (SN), perceived behavioral control (PBC), confidence in tourism recovery (CTR), and behavioral intention (BI). The third section collected socio-demographic information.

All constructs were adapted from established theories and prior studies (see Appendix A Table A1). The TPB constructs (ATTD, SN, PBC, and BI) were based on Ajzen's guidelines [77,78]. Questions were adjusted with the pandemic or tourism-based situations, as referenced by prior studies [29,79]. The CTR construct was adapted from Curtin (1982), Gurtner (2016), and Boukes et al. (2021) [80–82]. Responses were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

4.3. Pre-Test and Pilot Study

The questionnaire, originally in English, was translated into Chinese using the blind translation-back-translation method [83]. To ensure content and construct validity, the questionnaire was reviewed by three scholars and two field experts, leading to revisions for clarity. A pilot study with 204 respondents was conducted in mainland China using the Credamo platform (a survey provider in China specializing in collecting responses with 1.5 million qualified users.) in November 2022. Reliability for the constructs was assessed using Cronbach's alpha, with all constructs scoring above or near 0.7, except for PBC [84]. Items that did not meet reliability thresholds were removed, and quality control measures, such as minimum stay time and screening questions, were implemented to ensure valid responses.

4.4. Data Collection and Samples

Data collection was conducted through Credamo across eight provincial areas or cities of China (including Beijing, Tianjin, Henan, Shanghai, Zhejiang, Chongqing, Fujian, and Guangdong), with a small portion distributed offline. Given the evolving epidemic control measures, some questionnaire items were adjusted to ensure relevance to the respondents' current situation.

Three rounds of surveys were distributed between 25 December 2022 and 10 January 2023, resulting in 1026 valid responses after excluding low-quality or incomplete data. The sample was divided into three groups based on respondents' perceived stage of the pandemic: 330 respondents perceived the outbreak stage, 365 perceived stabilization, and 331 believed the pandemic had concluded.

4.5. Data Analysis

Data analysis included descriptive analysis of socio-demographic data using SPSS 23, hypothesis testing, and model evaluation using SmartPLS 4.0, a variance-based SEM technique widely used in marketing, management, and tourism research [85–88]. PLS-SEM was chosen for its predictive orientation and robustness in analyzing new constructs and complex models [88–91]. Moreover, PLS-MGA and IPMA are other advanced techniques we can use to achieve this study's objectives. Especially, while many researchers highlight that PLS-SEM works well with small sample sizes, PLS-SEM offers substantial potential for analyzing large datasets, which is the case in this study [92].

5. Results

5.1. Descriptive Statistics

5.1.1. Profile of Samples

A total of 1026 valid responses were analyzed, with the majority being female (70.7%), whereas males account for 29.3%. Most respondents were married (59.7%), while 39.3% were unmarried. The age distribution was concentrated between 21–30 years (44.6%) and 31–40 years (40.1%), and a significant portion had completed higher education (64.7% with undergraduate and 22.6% with graduate degrees). Occupations were primarily business-related (61.5%), and 57.3% of respondents reported monthly household incomes above 15,000 yuan (see more in Appendix A Table A2).

5.1.2. General Information About Travel Intention

This survey examined the impact of the pandemic on travel plans, post-pandemic travel intentions, and expenditure plans (as shown in Appendix A Table A3). Respondents were categorized into three phases based on their perception of the pandemic: outbreak (32.2%), stabilization (35.6%), and conclusion (32.3%), ensuring a balanced sample distribution. A significant 89.5% of respondents acknowledged that COVID-19 affected their travel plans, with 86.1% intending to travel within a year. Over half (53.3%) planned to increase their travel spending compared to pre-pandemic levels, while 17.9% expected to maintain their spending, and 15.3% intended to decrease it. Respondents primarily valued tourism for its ability to enhance well-being (22.7%), expand knowledge (20.5%), and provide spiritual experiences (19.8%), reflecting a shift in motivations since the pandemic began.

5.2. Model and Hypotheses Testing

As Henseler et al. (2009) [93] and Hair et al. (2012) [85] proposed, we evaluated the indicator reliability with outer loadings and Cronbach's α while the internal consistency reliability was assessed with Composite Reliability (CR). Convergent validity was analyzed with both CR and Average Variance Extracted (AVE), while discriminant validity was evaluated by using Average Variance Extracted (AVE) or by using the Heterotrait-monotrait (HTMT) Criterion. All the values were produced with SMARTPLS 4.0.

Table 1 summarizes the test for construct reliability and convergent validity. A total of 17 of the 19 items have outer loadings above 0.7. Only two of them exhibit slightly lower loadings of 0.653 and 0.643 but exceed the minimum cut of 0.5 [94]. Cronbach's α of every construct in this study is above the threshold of 0.7 [95]. Therefore, the indicator reliability can be confirmed in this study. Meanwhile, all CR values are above 0.7 with a minimum of 0.822, which indicates high internal consistency reliability. In addition, the AVE of each construct exceeds the suggested value of 0.5 with a minimum of 0.538 [96], indicating adequate convergent validity [97].

In terms of discriminant validity, which detects the degree of discrimination between tested variables and constructs, two commonly used methods were used in this study. As suggested by Fornell and Larcker (1981) [96], discriminant validity is obtained when the square root of each Average Variance Extracted (AVE) exceeds the correlation with other latent variables. As shown in Table 2, the square roots of the AVEs are higher than the off-diagonal correlations between the constructs, indicating sufficient levels of discriminant validity. Furthermore, another discriminant validity test was conducted using the Heterotrait-monotrait (HTMT) criterion, which had been proposed by Henseler et al. (2015) [98] and gradually developed as a preferred method for variance-based structural equation modeling (SEM). Table 3 demonstrates the HTMT values between the constructs, which are all below the conservative threshold of 0.85, as stated by Henseler et al. (2015) [98]. In addition, we conducted bootstrapping with 5000 sub-samples and found neither of the confidence interval values was below 1, which provided further support for discriminant validity.

Table 1. Construct reliability and validity.

Construct	Items	Loading	Cronbach's Alpha	CR	AVE
ATTD	ATTD_1	0.747	0.714	0.829	0.619
	ATTD_2	0.723			
	ATTD_3	0.881			
SN	SN_1	0.774	0.706	0.827	0.614
	SN_2	0.748			
	SN_3	0.827			
PBC	PBC_1	0.653	0.710	0.822	0.538
	PBC_2	0.643			
	PBC_3	0.792			
	PBC_4	0.828			
CTR	CTR_1	0.780	0.851	0.894	0.628
	CTR_2	0.720			
	CTR_3	0.849			
	CTR_4	0.820			
	CTR_5	0.786			
BI	BI_1	0.783	0.788	0.863	0.612
	BI_2	0.798			
	BI_3	0.800			
	BI_4	0.747			

Table 2. Discriminant validity (Fornell-Larcker criteria).

	ATTD	BI	CTR	PBC	SN
ATTD	0.787				
BI	0.176	0.782			
CTR	0.188	0.510	0.792		
PBC	0.187	0.473	0.384	0.734	
SN	0.224	0.433	0.330	0.355	0.784

Table 3. Discriminant validity (HTMT criteria).

	ATTD	BI	CTR	PBC	SN
ATTD					
BI	0.208				
CTR	0.230	0.620			
PBC	0.234	0.627	0.485		
SN	0.332	0.544	0.392	0.461	

Above all, based on the testing and evaluation, the results demonstrate that the scales used in this study have sufficient construct reliability and validity.

In addition, the PLS method requires no multicollinearity and no bias when assessing data from a composite model population [97]. This study uses variance inflation factor (VIF) values to assess the multicollinearity issues and common method bias (CMB). All constructs exhibit VIF values below the conservative threshold of 3.3, suggesting the absence of multicollinearity issues in the results [99]. The VIF values are summarized in Table 4. Kock (2015) [100] indicates that when all factor-level VIFs from a full collinearity assessment remain at or below 3.3, the model can be considered free from common method bias. In our study, all factor-level VIFs are below this threshold, indicating no evidence of such bias in these data.

Table 4. VIF values.

	VIF
ATTD -> BI	1.093
ATTD -> CTR	1.067
CTR -> BI	1.278
PBC -> BI	1.345
PBC -> CTR	1.160
SN -> BI	1.249
SN -> CTR	1.179

5.2.1. Structural Model

In relation to the evaluation of model fit in PLS path modeling, Henseler and Sarstedt (2013) argue that the Goodness-of-fit (GoF) indices are not appropriate for model validation [101]. However, as Henseler and Sarstedt (2011) suggested in detail, the Standardized Root Mean Square Residual (SRMR) could be used for analyzing the model fit of the Partial Least Squares (PLS) path models, and it was also appropriate for a PLS multi-group study with the same PLS path model [102]. Therefore, this study adopted the SRMR values to assess the adequacy of the model fit. The result shows that the SRMR values for the fully saturated model and the estimated model are 0.056 and 0.062, which are below the threshold of 0.08 and exhibit a satisfactory fit with empirical data [103].

As suggested by Hair et al. (2014), this study used the coefficient of determination (R^2) and Stone–Geisser’s Q^2 to analyze the explanatory power and predictive relevance of the model [104]. The R^2 and Q^2 values presented in Table 5 demonstrate the model’s satisfactory explanatory power. The R^2 value for BI indicates that its predictors account for 39.5% (>33%) of the variance in this construct, which could be considered moderate. Similarly, the R^2 value for CTR shows that 19.7% (>19% and <33%) of its variance is explained by its predictors, which was weak but acceptable. Meanwhile, Q^2 values of BI and CTR are both greater than zero, which indicates that the model has predictive relevance.

Table 5. Predictive validity and predictive relevance.

	R^2	Q^2
BI	0.395	0.293
CTR	0.197	0.189

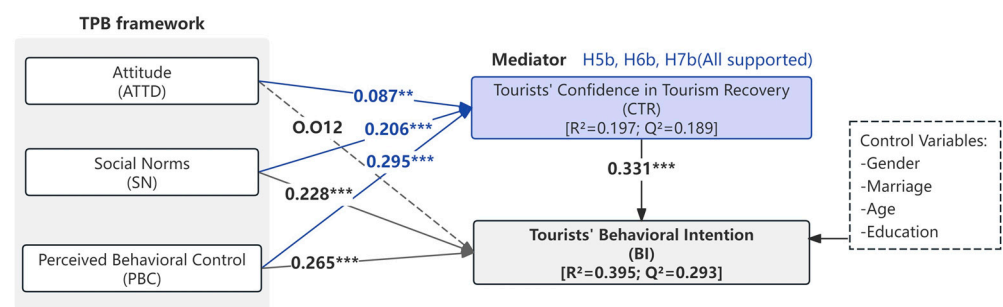
Path Coefficient Testing

This study employed a bootstrapping method with 5000 resamples to determine the statistical significance of the path coefficients, which are assessed to test the hypothesized relationships between latent variables. The significance level utilized in this research is five, which denotes that the hypothesized relationship is deemed to be significantly influential when the t-value is above 1.96 [97]. As illustrated in Table 6, both SN ($\beta = 0.228$, $T = 6.491$, $p < 0.001$) and PBC ($\beta = 0.265$, $T = 7.620$, $p < 0.001$) have a significant and positive relationship with BI, while ATTD ($\beta = 0.012$, $T = 0.457$, $p > 0.05$) is not statistically related to BI. Therefore, H2 and H3 are supported, while H1 is not supported. Concerning CTR, the findings reveal that CTR has a significant and positive relationship with BI ($\beta = 0.331$, $T = 9.518$, $p < 0.001$), which confirms H4. In addition, statistics also show that ATTD ($\beta = 0.087$, $T = 2.902$, $p < 0.005$), SN ($\beta = 0.206$, $T = 5.519$, $p < 0.001$), PBC ($\beta = 0.295$, $T = 8.552$, $p < 0.001$) demonstrate a positive relationship with CTR, which support H5a, H6a, and H7a respectively. Above all, Figure 2 shows the hypothetical models.

Table 6. Hypothesis testing.

Hypothesis	Path	Std. β	T Value	p-Value
H1	ATTD -> BI	0.012	0.457	0.648
H2	SN -> BI	0.228 ***	6.491	0.000
H3	PBC -> BI	0.265 ***	7.620	0.000
H4	CTR -> BI	0.331 ***	9.518	0.000
H5a	ATTD -> CTR	0.087 **	2.902	0.004
H6a	SN -> CTR	0.206 ***	5.519	0.000
H7a	PBC -> CTR	0.295 ***	8.552	0.000

Note: Significance level: ** $p < 0.01$, *** $p < 0.001$.



Note: Significance level: ** $p < 0.01$, *** $p < 0.001$.

Figure 2. Results of structural modeling analysis.

5.2.2. Mediating Effect of Confidence in Tourism Recovery (CTR)

To verify H5b, H6b, and H7b, the mediating role of CTR in the original framework of TPB, Variance Accounted For (VAF), is introduced in the data analysis (as shown in Table 7). According to Hair et al. (2014) [104], VAF is a crucial metric to qualify the proportion of the total effect that is mediated through the mediator variable. As discussed above, the direct effect of ATTD on BI (H1) is found to be non-significant. When CTR is introduced as a mediator, the indirect effect of ATTD on BI becomes significant. The VAF was calculated to be 71% (larger than 20% but smaller than 80%), revealing that the mediation of CTR on the relationship between ATTD and BI can be confirmed as partial mediation. In other words, 71% of the total effect of ATTD on BI is mediated by CTR, while 29% of the effect is direct. Similarly, when CTR mediates SN and BI, or PBC and BI, VAF values are calculated as 23% and 27%, respectively, which reveals a partial mediation effect as well. Hence, H5b, H6b, and H7b are all supported.

Table 7. Mediation analysis.

Relationships	Indirect Effect	T	p	Direct Effect	T	p	VAF	Mediation Type	Hypothesis Testing
Mediation effect of CTR									
H5b: ATTD -> CTR -> BI	0.029	2.775	0.006	0.012	0.457	0.648	71%	PM	Supported
H6b: SN -> CTR -> BI	0.068	4.602	0.000	0.228	6.491	0.000	23%	PM	Supported
H7b: PBC -> CTR -> BI	0.098	6.446	0.000	0.265	7.620	0.000	27%	PM	Supported

Note: T represents two-tailed T-test values; p denotes significance level; VAF, Variance Accounted For; PM, Partial Mediation; NM, No Mediation.

5.3. Multi-Group Comparison

In the current study, we have chosen to employ the MICOM (Measurement Invariance of Composite Models) combined with the IPMA (Importance–Performance Matrix Analysis) method to analyze the differences across different time points. The MICOM procedure allows us to rigorously test for measurement invariance across groups, thereby

ensuring that any observed differences in IPMA results are not due to inconsistencies in how constructs are measured over time [97,105]. Following the validation of measurement invariance, we can compare the IPMA results across the three sample groups to gain a deeper understanding of how different variables influence travel intentions during various stages of the pandemic's development, which is based on the assessment of not only the performance but also relative importance of each construct [106].

5.3.1. Measurement Invariance Testing

First, we paired the three sample groups for pairwise comparisons (see Table 8 for details). Following the MICOM procedure, the first step tested for configural invariance. Since the model's structure was consistent, this step was fully passed. The second and third steps were analyzed using the permutation MGA results in SmartPLS 4.0. The second step yielded the compositional invariance results, which, as shown in Table 8, were fully passed, with each pairwise comparison achieving partial invariance. The third step provided the mean invariance and variance invariance results, where some variables exhibited significant differences between groups. Based on the results of the second and third steps, we can proceed with the comparison of intergroup differences [105].

Table 8. MGA analysis.

Constructs	Comparison Group	Configural Invariance	Compositional Invariance (<i>p</i> -Value)	Mean Invariance (<i>p</i> -Value)	Variance Invariance (<i>p</i> -Value)	Measurement Invariance Conclusion
ATTD	Group 1 vs. Group 2	Passed	0.111	0.158	0.913	Fully Passed
	Group 1 vs. Group 3	Passed	0.164	0.722	0.659	Fully Passed
	Group 2 vs. Group 3	Passed	0.543	0.105	0.752	Fully Passed
SN	Group 1 vs. Group 2	Passed	0.122	0.012	0.025	Partially Passed
	Group 1 vs. Group 3	Passed	0.421	0.008	0.409	Partially Passed
	Group 2 vs. Group 3	Passed	0.534	0.467	0.171	Fully Passed
PBC	Group 1 vs. Group 2	Passed	0.483	0.752	0.495	Fully Passed
	Group 1 vs. Group 3	Passed	0.431	0.016	0.239	Partially Passed
	Group 2 vs. Group 3	Passed	0.464	0.024	0.639	Partially Passed
CTR	Group 1 vs. Group 2	Passed	0.383	0.001	0.021	Partially Passed
	Group 1 vs. Group 3	Passed	0.768	0.000	0.022	Partially Passed
	Group 2 vs. Group 3	Passed	0.374	0.005	0.959	Partially Passed
BI	Group 1 vs. Group 2	Passed	0.142	0.000	0.021	Partially Passed
	Group 1 vs. Group 3	Passed	0.187	0.000	0.000	Partially Passed
	Group 2 vs. Group 3	Passed	0.905	0.000	0.323	Partially Passed

5.3.2. IPMA Analysis and Comparison

Secondly, this study employed the Importance–Performance Map Analysis (IPMA) to understand how the importance and performance of different variables related to travel intentions vary across the three sample groups (as shown in Table 9). The analysis was conducted using SmartPLS 4.0, and the importance scores reflect the relative influence of each variable on tourists' Behavioral Intentions (BI), while the performance scores represent how well each variable is perceived by the respondents in each group.

Table 9. IPMA results.

Predictor Constructs	Group1		Group2		Group3	
	Importance (X)	Performance (Y)	Importance (X)	Performance (Y)	Importance (X)	Performance (Y)
ATTD	0.039	85.545	0.087	83.341	0.039	85.801
CTR	0.352	67.952	0.304	72.402	0.301	74.409
PBC	0.261	71.984	0.411	73.429	0.426	76.335
SN	0.330	73.66	0.285	75.888	0.238	77.079
Mean values	0.246	74.785	0.272	76.265	0.251	78.406

Figures 3–5 show the IPMA results of Groups 1, 2, and 3, respectively. According to Ringle, et al. (2016) [106] and Irimia-Diéguez, Ana, et al. (2023) [107], when examining the Importance–Performance Map, constructs located in the lower-right quadrant, indicating above-average importance but below-average performance, present the most promising opportunities for improvement. These are followed in priority by constructs in the upper-right, lower-left, and, finally, the upper-left quadrants.

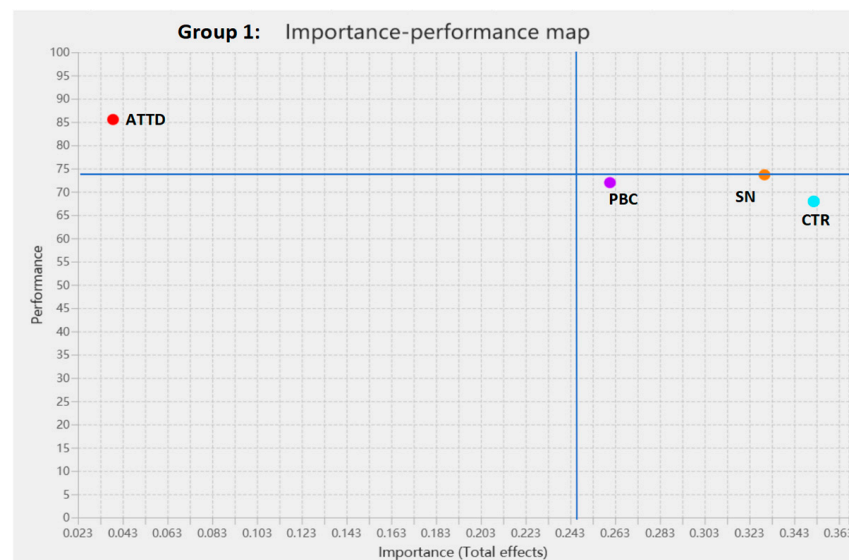


Figure 3. Importance–Performance Map for Group 1 (Outbreak Phase).

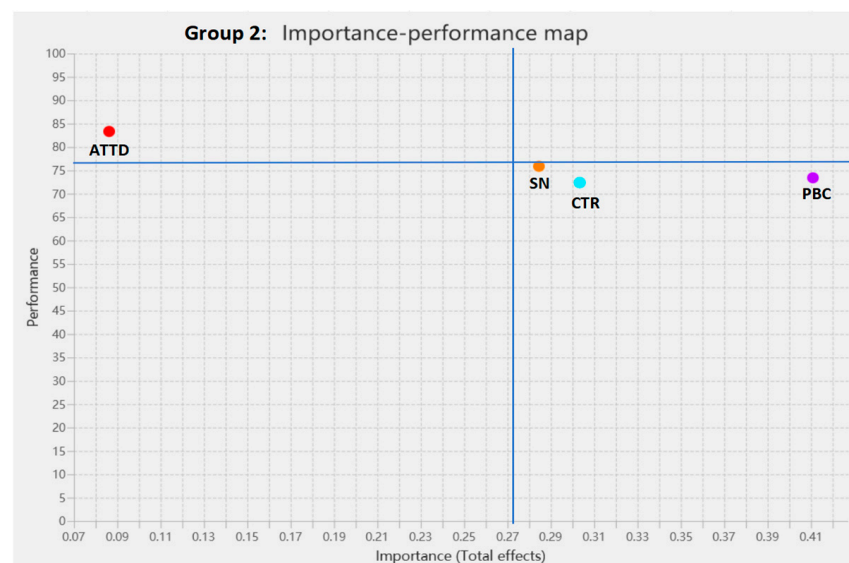


Figure 4. Importance–Performance Map for Group 2 (Stabilization Phase).

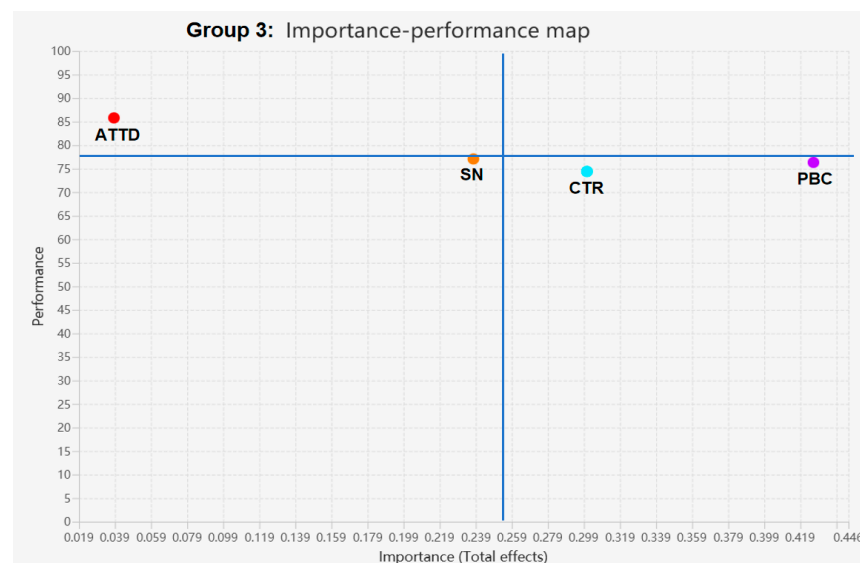


Figure 5. Importance–Performance Map for Group 3 (Conclusion Phase).

In the first group, representing the perceived pandemic outbreak stage, the variables CTR, PBC, and SN fall into the lower-right quadrant, among which CTR emerged with the highest importance but exhibited relatively low performance. This indicates a critical area for improvement. In the second group, corresponding to the stabilization phase, the variables CTR, PBC, and SN are still located in the lower-right quadrant. In contrast, the importance ranking of the three variables in the lower-right quadrant of the second group has changed, with PBC showing the highest importance, followed by CTR and SN. Finally, the third group, representing the conclusion of the pandemic, saw a shift in importance towards SN, which is located in the lower-left quadrant. PBC and CTR remain in the lower-right quadrant and PBC still calls for the most attention to be improved. The variable ATTD, across the three groups, has consistently remained in the same position in the upper-left quadrant. Above all, these findings suggest that tourism management strategies should be dynamic and responsive to the changing priorities of travelers as the pandemic evolves.

6. Discussion and Implications

This study accomplished two primary research objectives: first, it introduced the concept of Confidence in Tourism Recovery (CTR) as a mediating variable within the Theory of Planned Behavior (TPB) model, investigating how the relationships between Attitude (ATTD), Subjective Norm (SN), and Perceived Behavioral Control (PBC) and travel intentions (BI) change in the context of a public health crisis, such as a pandemic. Second, by comparing samples from different stages of the pandemic, this study provided insights for governments and businesses to develop strategies that adapt to the dynamic changes in tourism demand. The main findings and implications of this study can be summarized as follows.

6.1. Main Findings

6.1.1. Impact of Confidence in Tourism Recovery (CTR) on Travel Intentions

This study empirically confirmed that CTR has a direct positive impact on travel intentions (BI) and serves as a mediator for the effects of ATTD, SN, and PBC on BI. Data from the overall sample demonstrated a strong correlation between CTR and BI, with a path coefficient of 0.331. This indicates that in the specific context of a pandemic, travel intentions are influenced not only by negative factors, such as perceived risk and travel restrictions but also by positive factors, such as confidence in the recovery of the tourism industry. This finding aligns with previous research [30,108]. Enhancing CTR

can effectively stimulate travel intentions and aid in the recovery of the tourism industry. Additionally, this study revealed that CTR plays a significant role as a mediator in the pathways by which ATTD, SN, and PBC influence BI. Specifically, CTR accounted for 71% of the effect of ATTD on BI, 23% of the effect of SN on BI, and 27% of the effect of PBC on BI, indicating a strong amplifying effect. This suggests that CTR is a crucial variable for predicting and stimulating travel intentions in the context of a pandemic, as it can enhance the predictive power of traditional TPB variables when they might otherwise fail under such circumstances. Furthermore, because CTR is more susceptible to the influence of industry recovery policies and marketing strategies, this finding is particularly valuable for improving management practices. Across the three groups of samples from different pandemic stages, CTR consistently appeared in the lower-right quadrant of the IPMA analysis, indicating that it is a variable with potential that requires focused improvement.

6.1.2. Impact of Tourism Attitudes on Travel Intentions

This study found that under pandemic conditions, the direct effect of ATTD on BI is not significant, with CTR explaining 71% of the impact of ATTD on BI. This suggests that attitudes toward tourism are relatively stable and long-term, while travel intentions are more dynamic and influenced by a broader range of factors, particularly in crisis contexts. This distinction can help explain why our results show that attitudes did not have a significant direct impact on travel intentions during the pandemic. This finding aligns with Ajzen's Theory of Planned Behavior (TPB), which suggests that while attitudes are important, their predictive power can vary depending on the context [37]. Juschten et al. (2019) also highlighted that attitudes may not always serve as reliable predictors of intentions, especially in situations where external factors play a dominant role [109].

Additionally, we have found in Multi-Group Analysis (MGA) (see Table 8 for details) that the means and variances of tourism attitudes across the three sample groups showed no significant differences, indicating that attitudes toward tourism did not change with the progression of the pandemic. As for travel intention (the construct BI), the research results revealed significant differences in mean invariance for most group comparisons (p -values below 0.05), indicating that average travel intentions varied across groups. Additionally, the variance invariance test showed that, except for the comparison between Group 2 and Group 3 ($p = 0.323$), all other group comparisons indicated significant differences in variance, suggesting different levels of variability in travel intentions across groups. These findings highlight how different stages of the pandemic influenced both the average levels and the variability of travel intentions, whereas attitudes toward tourism remained stable. Descriptive statistics from this study indicate that respondents generally held positive attitudes toward travel, with most expressing a willingness to travel post-pandemic and maintain or increase their travel spending. In summary, the introduction of CTR as a mediator provides new insights into how crisis-induced variables can reshape the pathways from attitudes to behavior. It reveals that increasing CTR levels can help positive tourism attitudes translate more quickly into travel intentions, which is crucial for the recovery of tourism consumption post-pandemic.

6.1.3. Impact of Subjective Norms on Travel Intentions

In this study, SN had a significant positive direct effect on BI, with a path coefficient of 0.228. SN represents external influences on travelers, and research has shown that people are aware of pandemic prevention measures, including movement restrictions and social distancing. They may face social pressure, and SN was previously a major driver of travel intentions [16]. This study also confirmed the positive impact of SN on BI in the context of a pandemic. Furthermore, this study examined the mediating role of CTR in the relationship between SN and BI. Enhancing CTR can also increase the influence of SN on BI to some extent.

Additionally, IPMA analysis of three sample groups revealed that the importance of SN in influencing BI gradually decreased from the outbreak to the stabilization and end of

the pandemic. However, the differences in performance were not significant. In the IPMA chart, SN shifted from the lower-right quadrant to the lower-left quadrant over time. This trend can be explained by the fact that as the pandemic progressed, individuals relied less on social cues and more on personal confidence in the recovery of the tourism industry and their own ability to travel. This reflects a transition from externally driven behavior (influenced by social pressures) to internally motivated behavior, where individuals make travel decisions based on their personal confidence and risk assessments. This nuanced understanding of the evolving role of SN provides new insights into travel behavior models, particularly during disruptive events such as the pandemic.

6.1.4. Impact of Perceived Behavioral Control on Travel Intentions

This study also found that PBC had a significant positive direct effect on BI, with a path coefficient of 0.265. According to the Theory of Planned Behavior, PBC directly influences behavioral intentions and, subsequently, actual behavior. PBC reflects individuals' perceived ability and resources to engage in a particular behavior [20]. This study further confirmed the mediating effect of CTR through empirical data. This suggests that when travelers' confidence in the recovery of the tourism industry increases, this confidence can alleviate their concerns about risk, enhance their PBC, and, in turn, strengthen their travel intentions. The IPMA analysis of the three sample groups also revealed that the importance of PBC in influencing BI increased from the outbreak to the stabilization and end of the pandemic. However, the differences in performance were not significant. This trend was the opposite of SN. In the IPMA chart, PBC consistently appeared in the lower-right quadrant, with its importance ranking first in the second and third groups, indicating that it is the most promising variable requiring improvement.

6.2. Managerial Implication

This study empirically verified the importance of CTR in restoring travel intentions and demonstrated the dynamic changes in factors influencing travel intentions across different stages of the pandemic through data tracking. These findings provide significant insights for government agencies and tourism enterprises. Based on this, we summarize the policies and measures that governments and businesses can adopt at different stages of the pandemic as follows:

6.2.1. Policies and Measures during the Outbreak Stage

During the initial outbreak stage, government control measures were intensified, and travelers' perceived risk of travel significantly increased. The tourism industry was severely affected, and travelers developed strong doubts about the safety of tourism activities, leading to widespread cancellations and postponements [110]. At this stage, travelers' confidence in tourism recovery was at its lowest. However, this study's findings indicate that CTR at this stage had the greatest potential for improvement. According to IPMA analysis, CTR was the variable most in need of policy intervention, followed by SN and PBC.

From a government perspective, implementing strict and effective travel restrictions, quarantine requirements, and public health measures can build traveler trust and enhance CTR levels. This will lay a solid foundation for travelers to rebuild confidence and resume travel activities post-pandemic. Additionally, government financial support and subsidies for the tourism industry, along with public promotion of the industry's recovery potential and positive outlook, can also enhance CTR levels, contributing to the recovery of the tourism market post-pandemic. In response to COVID-19, fiscal support measures were taken by the government for tourism businesses during the outbreak stage, including tax reductions and exemptions. However, there was a lack of sustained support to ensure the industry's full recovery. Additionally, government agencies might overlook promoting the recovery potential of the tourism sector to travelers, which is critical for maintaining their confidence. These are areas that should be addressed and improved in the future.

From a business perspective, adopting flexible cancellation and refund policies during the crisis can help travelers mitigate economic losses due to force majeure and establish a responsible corporate image. By improving CTR levels, businesses can reduce the negative psychological impact of the crisis on travelers. Furthermore, tourism enterprises should actively cooperate with the government in implementing strict sanitation and safety protocols, showcasing their crisis management capabilities and positive public brand image. This not only enhances CTR but also improves SN and PBC levels, mitigating the negative effects of the crisis.

6.2.2. Policies and Measures during the Stabilization Stage

As the pandemic is brought under a certain level of control, travelers' confidence gradually begins to recover. Kock et al. (2020) found that during this stage, travelers start reconsidering short-distance travel and domestic tourism [111]. The IPMA analysis results of this study indicate that at this stage, the importance of PBC surpassed CTR, ranking first, with CTR second and SN third. The findings suggest that during this stage, people are more concerned about whether they can successfully engage in tourism activities. While CTR levels improved, their importance diminished.

From a government perspective, travel restrictions can be gradually relaxed, starting with short-distance and domestic tourism activities and progressively reopening low-risk tourist destinations. Additionally, special funds and support programs can be introduced to encourage tourism enterprises to develop safer and more innovative tourism products in response to market changes.

From a business perspective, the development and promotion of "safe travel" brands, such as small group tours, customized private tours, and outdoor wellness tours, can meet travelers' safety needs. Utilizing social media and digital platforms to strengthen communication with potential tourists, and sharing safe travel cases and positive reviews can enhance trust. These measures can more effectively improve PBC and CTR levels, thereby maintaining and stimulating tourism demand, which is beneficial for the sustainable recovery of the tourism market.

6.2.3. Policies and Measures during the Post-Pandemic Stage

Once the pandemic is effectively controlled or ends, travelers' confidence will quickly rebound. Related research indicates that during this stage, travel intentions increase significantly, especially for long-distance and international travel [8]. However, behavioral patterns and preferences may undergo long-term changes, such as a greater focus on health and safety and a preference for more personalized travel experiences [47]. Descriptive statistics and IPMA analysis of this study show that during this stage, PBC and CTR remain key variables requiring improvement, while the importance of SN in influencing travel intentions diminishes. Travelers are more focused on meeting and fulfilling their travel needs.

From a government perspective, once the pandemic is under control, full-scale resumption of domestic and international tourism activities should be implemented, with all remaining travel restrictions lifted. A long-term but agile public crisis response mechanism should be established to address the uncertainty of future crises. Additionally, collaborating with international organizations and other countries to promote safe international travel and attract foreign tourists back to the domestic market can help quickly rebuild confidence among international and domestic tourists, making it easier to translate travel intentions into travel behavior. At the same time, during the next crisis, these measures can help reduce the negative effects of anxiety and fear. Furthermore, government agencies should formulate long-term strategies focused on sustainable tourism recovery. These may include Infrastructure investment to support evolving traveler needs, talent development programs to ensure the sector remains competitive, and market promotion aimed at highlighting the resilience and adaptability of the tourism sector, helping to solidify the recovery process.

From a business perspective, attention should be paid to the long-term impact of the pandemic on tourism demand, including shifts in travelers' habits and preferences. Developing health-focused and personalized tourism products is essential. Our research shows that travelers are still very concerned about the safety of travel during this stage. Therefore, reinforcing the brand's safety and reliability image has a greater impact on travelers. Additionally, given the continued influence of CTR during this stage, tourism enterprises can introduce new technologies and services, such as virtual reality experiences and intelligent travel guides, to enhance the overall experience of tourists and improve CTR levels, thereby strengthening relationships with travelers.

In conclusion, through these measures, governments and businesses can effectively boost traveler confidence at different stages of the pandemic, driving the sustained recovery and development of the tourism industry.

7. Conclusions, Limitations and Future Research

This study explores the mediating role of Confidence in Tourism Recovery (CTR) in the relationship between Tourism Attitude (ATTD), Subjective Norm (SN), Perceived Behavioral Control (PBC), and Behavioral Intention (BI) to travel in the context of the pandemic. The findings reveal that CTR has a significant positive impact on travel intentions and serves as a key mediator in the pathways between ATTD, SN, and PBC toward BI, especially when attitudes exert a weaker influence on travel intentions. Moreover, this study, through data analysis across different pandemic stages, demonstrates that the influence of CTR, SN, and PBC on travel intentions changes dynamically as the pandemic progresses. The results provide governments and tourism enterprises with valuable insights for formulating targeted recovery strategies and marketing approaches at various stages of the pandemic, emphasizing the importance of enhancing travelers' confidence in the industry's recovery. By implementing effective policies and measures, governments and businesses can boost traveler confidence across different phases of the pandemic, thereby promoting the sustained recovery and development of the tourism industry.

Despite the efforts made in this study to accurately reflect the real conditions of the pandemic in the research design, data collection, and analysis, with the aim of capturing respondents' genuine psychological responses, there are areas for improvement concerning the randomness and representativeness of the sample. For example, the final sample contained a higher proportion of female respondents compared to male respondents. Although age variables were controlled for, minor biases still exist. Future research could aim to control gender ratios to match real population distributions better. Furthermore, although three rounds of surveys were conducted to capture people's psychological feedback at different stages of the pandemic, the unpredictability of pandemic phases—along with regional differences in progression—may have led to some biases. Specifically, the transition from the stabilization phase to the end of the pandemic was relatively brief, potentially missing some critical findings. Future research could consider collecting data six months, one year, and two years after the pandemic's conclusion to track psychological changes during tourism recovery and explore the dynamic changes in the mechanisms influencing travel intentions in the post-pandemic era, thereby extending the results of this study.

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Informed Consent Statement: In accordance with ethical requirements, informed consent was obtained from all participants involved in this study.

Data Availability Statement: Data that support the findings of this study are available from the corresponding author upon request. Due to privacy concerns and restrictions imposed by the online survey platform, which requires user authentication for access, the raw survey data cannot be made publicly available.

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Appendix A

Table A1. Constructs and Measurement Items.

Constructs (Latent Variables)	Items	Measurement	Reference
Attitude (ATTD)	Conceptualization: There are differences in people’s attitudes towards travel activities. As a tourist, to what extent do you agree with the following statements about travel attitudes?		
	ATTD1	I think travel activities are helpful to me	[77,78]
	ATTD2	I think travel activities can make me happy.	
	ATTD3	I think travel activities can enrich my life experience.	
Subjective Norms (SN)	Conceptualization: When people travel, they often consider the opinions and ideas of people or institutions that are important to them, which we call subjective norms. To what extent do you agree with the following statements about subjective norms?		
	SN1	I prefer to travel if those who are important to me (family, friends, colleagues, neighbors, etc.) approve of my travel.	[29,78]
	SN2	I prefer to travel if those who are important to me (family, friends, colleagues, neighbors, etc.) allow me to travel.	
	SN3	I prefer to travel if those who are important to me (family, friends, colleagues, neighbors, etc.) give me time or money to support me.	
Perceived Behavioral Control (PBC)	Conceptualization: When people travel, they often consider their own conditions and the control of future behavior, which we call perceived behavioral control. To what extent do you agree with the following statement about perceived behavioral control?		
	PBC1	I have the basic conditions to travel (such as my income, time, and health conditions allow me to travel)	[29]
	PBC2	I can make travel preparations according to the epidemic situation at the destination (such as preparing epidemic prevention items and accordingly making travel arrangements).	
	PBC2	I can deal with all kinds of emergencies related to the epidemic in the process of traveling (such as medical treatment due to infection, temporary closure of scenic spots, cancellation of tourist activities, etc.).	
	PBC3	I can bear the consequences of the epidemic during the trip (such as the health impact and additional medical expenses caused by the infection during the trip, the material and spiritual losses caused by the cancellation of travel activities, and other additional losses caused by other emergencies).	

Table A1. Cont.

Constructs (Latent Variables)	Items	Measurement	Reference
Confidence in Tourism Recovery (CTR)	Conceptualization: Are you confident about the recovery of the tourism industry? To what extent do you agree with the following statements about the restoration of confidence in the tourism industry?		
	CTR1	I think the tourism industry will recover quickly after the epidemic.	[80–82]
	CTR2	I believe that the government’s policies and measures for the revitalization and recovery of tourism will promote the rapid recovery of tourism.	
	CTR3	I think the scale of tourism will quickly recover to the level before the epidemic (2019).	
	CTR4	I think the ability of tourism enterprises to provide products will recover quickly.	
	CTR5	If I were an investor, I would buy shares of listed companies in the tourism industry.	
Behavioral Intention (BI)	Conceptualization: (In Chinese, the concept of travel intentions could be understood literally; thus no extra explanation here). To what extent do you agree with the following statements about travel intentions?		
	BI1	Although affected by the epidemic, I have plans to travel.	[78,79]
	BI2	I will go out to travel recently.	
	BI3	I will encourage and support people around me to travel.	
	BI4	I would recommend tourist destinations to people around.	

Table A2. Respondents’ profile.

Characteristics	Classification	Frequency	Percentage
Gender	Male	301	29.3%
	Female	725	70.7%
Marital Status	Unmarried	403	39.3%
	Married	613	59.7%
	Others (divorced, separated, or widowed)	10	1%
Age (years)	<20	54	5.3%
	21–30	458	44.6%
	31–40	411	40.1%
	41–50	66	6.4%
	51–60	35	3.4%
	>60	2	0.2%
Education Level	Secondary school and below	8	0.8%
	High school/Technical school/Vocational school	29	2.8%
	Technical college	93	9.1%
	Undergraduate college	664	64.7%
	Graduate college	232	22.6%
Occupation	Government agency/institution official	17	1.7%
	Government agency/institution staff	46	4.5%
	State-owned business/enterprise manager	106	10.3%
	State-owned business/enterprise staff	105	10.2%
	Private or foreign-funded business/enterprise manager	224	21.8%
	Private or foreign-funded business/enterprise manager staff	197	19.2%
	Professional/technician/teacher/doctor/lawyer	86	8.4%
	Private business owner	27	2.6%
	Self-employed	22	2.1%
	Farmer	1	0.1%
	Student	181	17.6%
	Retiree	4	0.4%
	Others	10	1%

Table A2. Cont.

Characteristics	Classification	Frequency	Percentage
Family Member	1 person	28	2.7%
	2 people	55	5.4%
	3 people	363	35.4%
	4 people	309	30.1%
	5 people	184	17.9%
	6 people	68	6.6%
	More than 6 people	19	1.9%
Average Monthly Household Income	Less than 3000 yuan	19	1.9%
	3001–6000 yuan	77	7.5%
	6001–9000 yuan	116	11.3%
	9001–12,000 yuan	105	10.2%
	12,001–15,000 yuan	122	11.9%
	15,001–18,000 yuan	117	11.4%
	18,001–21,000 yuan	128	12.5%
	21,001–24,000 yuan	87	8.5%
	24,001–27,000 yuan	49	4.8%
	27,001–30,000 yuan	72	7%
	More than 30,000 yuan	134	13.1%

Table A3. General information about travel intention.

Questions	Options	Frequency	Percentage
In which phase of the epidemic do you believe your city is presently situated?	The outbreak	330	32.2%
	The stabilization	365	35.6%
	The conclusion	331	32.3%
Has the COVID-19 pandemic had an impact on your travel arrangements or the execution of your travel plans?	Yes	918	89.5%
	No	108	10.5%
How soon will you travel?	Within a month	141	13.7%
	Within one to three months	362	35.3%
	Within three months to one year	381	37.1%
	A year later	97	9.5%
	No plan	45	4.4%
How will your expenses change if you travel compared to before the epidemic?	Increase	547	53.3%
	Reduce	157	15.3%
	Unchanged	184	17.9%
	Not sure	93	9.1%
	Missing	45	4.4%
* What do you believe you can benefit from traveling?	Pleasure body and mind	939	22.70% (91.50%)
	Obtain spiritual experience	818	19.80% (79.70%)
	Increase knowledge and expand the horizon	848	20.50% (82.70%)
	Improve relationships with friends and family	654	15.80% (63.70%)
	Fulfill the intention of rest and vacation	447	10.80% (43.60%)
	Improve one's social status	141	3.40% (13.70%)
	Expand the circle of friends	283	6.80% (27.60%)
	Others	2	0.00% (0.20%)

Note: The question marked with “*” is a multiple-choice question. The unenclosed percentage number denotes the proportion of selecting a particular option's frequency in relation to the entire frequency, while the percentage in bracket signifies a particular option's frequency in relation to the total number of respondents.

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