future transportation

MDPI

Article

Implications of the China–Pakistan Economic Corridor on Domestic and Cross-Border Travel Willingness

Yousaf Ali [1], Jing Shi [1,*] and Muhammad Hussain [2]

[1] Institute of Transportation Engineering, Tsinghua University, Beijing 100084, China; engryousaf87@gmail.com
[2] Western Australian Centre for Road Safety Research, School of Psychological Science, University of Western Australia, 35 Stirling Highway, Perth, WA 6009, Australia; muhammad.hussain@uwa.edu.au
* Correspondence: jingshi@tsinghua.edu.cn; Tel.: +86-10-62772

Abstract

The China–Pakistan Economic Corridor (CPEC) represents a transformative transport infrastructure initiative with the potential to reshape tourism in South Asia. However, the behavioral mechanisms through which corridor development translate into travel willingness remain insufficiently understood, particularly between domestic and cross-border tourism. This study investigated the determinants of domestic tourism willingness within Pakistan and cross-border tourism willingness toward China using a stated preference survey of 441 Pakistani respondents collected through an online questionnaire. To balance behavioral interpretation and predictive performance, this study integrated ordinal logistic regression (OLR) with multiple machine learning classifiers. The results revealed clear behavioral asymmetries between domestic and cross-border tourism decisions. Domestic tourism willingness was primarily driven by attitudinal evaluations, particularly perceived desirability, pleasantness, and comfort of travel along the CPEC. In contrast, cross-border tourism willingness was more strongly constrained by knowledge-related and institutional factors, including awareness of visa procedures, accommodation arrangements, and destination information. Comparative performance analysis indicated that machine learning models outperformed ordinal logistic regression, improving predictive accuracy by approximately 12.6 percentage points for domestic tourism (93.6% vs. 81.0%) and 1.7 percentage points for cross-border tourism (81.1% vs. 79.4%). These findings demonstrate that corridor-induced tourism demand is governed by distinct behavioral mechanisms across domestic and international contexts, highlighting the need for differentiated tourism development strategies. From a policy perspective, the results suggest that domestic tourism development along the CPEC should prioritize experiential quality and travel comfort, whereas cross-border tourism promotion should focus on reducing informational and procedural barriers such as visa knowledge, accommodation awareness, and travel facilitation.

Keywords: tourism willingness; transport corridors; China–Pakistan Economic Corridor; travel behavior; ordinal logistic regression; machine learning; cross-border tourism

Check for updates

Academic Editor: Luigi dell'Olio

Received: 2 March 2026
Revised: 19 March 2026
Accepted: 23 March 2026
Published: 29 March 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

The China–Pakistan Economic Corridor (CPEC) represents one of the most significant corridor-based infrastructure initiatives in South Asia, with the potential to reshape not only trade and logistics but also patterns of tourism mobility [1]. By improving connectivity, reducing travel time, and enhancing access to diverse destinations, the CPEC is expected to influence how travelers perceive the feasibility, attractiveness, and utility

of undertaking tourism trips. However, transport infrastructure does not automatically translate into increased travel demand. From a travel behavior perspective, infrastructure improvements must be mediated through travelers' perceptions, attitudes, knowledge, and socio-demographic constraints before they manifest as willingness to travel [2]. These behavioral mechanisms are particularly salient for tourism, which is discretionary in nature and sensitive to perceived comfort, safety, information availability, and social context [3].

Despite the strategic importance of CPEC, existing research on its tourism implications remains limited in several important respects. Much of the current literature is dominated by conceptual discussions, desk-based analyses, and qualitative assessments that emphasize potential benefits, regional development, or infrastructure provision, with relatively little emphasis on individual-level travel behavior [4–6]. As a result, empirical evidence explaining how travelers form tourism willingness judgments in response to corridor-based infrastructure development remains limited, particularly in the context of Pakistan.

Another important gap in literature concerns the distinction between domestic and cross-border tourism behavior. Domestic tourism decisions are typically influenced by experiential and attitudinal factors such as pleasantness, comfort, and social travel conditions [7,8]. In contrast, cross-border tourism involves additional institutional and informational barriers, including visa requirements, procedural uncertainty, accommodation arrangements, and perceived safety in foreign destinations [9–11]. Consequently, the behavioral mechanisms underlying domestic and international tourism decisions may differ substantially. Treating domestic and cross-border tourism as behaviorally equivalent risks oversimplifying corridor-induced tourism demand and may lead to ineffective tourism policy interventions.

A further limitation of existing studies lies in the inadequate representation of behavioral complexity in quantitative modeling. Willingness to travel is influenced not only by observable socio-demographic characteristics but also by attitudes, perceptions of comfort and safety, subjective knowledge, and prior travel experience [2]. Similar findings have been reported in the context of autonomous mobility services and shared autonomous vehicles, where socio-demographic characteristics, perceived service quality, and infrastructural factors significantly influenced willingness to adopt emerging mobility systems [12,13]. Traditional modeling approaches often impose linear and additive structures that may fail to capture non-linear effects, interaction mechanisms, and threshold behavior, which are especially relevant in corridor settings and in cross-border travel where institutional constraints may act as binding conditions [14].

Furthermore, tourism behavior research has rarely integrated econometric and machine learning approaches within a single analytical framework. Econometric models such as ordinal logistic regression are widely used for behavioral interpretation and hypothesis testing [15], while machine learning models offer superior flexibility in capturing non-linear relationships and complex interaction effects [16]. However, relatively few studies have systematically compared these approaches using the same behavioral dataset. Consequently, the relative explanatory and predictive advantages of these modeling approaches remain unclear, particularly in emerging tourism contexts such as transport corridor development. Together, these studies suggest that tourism travel willingness is shaped by both structural infrastructure conditions and behavioral perceptions, highlighting the need for integrated analytical frameworks that combine behavioral interpretation with predictive modeling approaches.

Against this backdrop, the present study addresses the lack of empirically grounded and behaviorally informed evidence on how CPEC influences tourism travel willingness in both domestic and cross-border contexts. Specifically, the study investigates the determinants of tourism willingness among Pakistani travelers and compares the behavioral

mechanisms underlying domestic tourism within Pakistan and cross-border tourism toward China.

By integrating ordinal logistic regression with multiple machine learning algorithms and conducting a comparative performance evaluation using metrics such as accuracy, recall, F1-score, and ROC curves, this study bridges the gap between behavioral explanation and predictive modeling.

This study makes three main contributions. First, it provides empirical evidence on tourism travel willingness in the context of a major transport corridor initiative. Second, it demonstrates that domestic and cross-border tourism willingness are governed by distinct behavioral mechanisms. Third, it illustrates the complementary value of combining econometric and machine learning approaches in tourism behavior research. Together, these contributions provide a more nuanced understanding of corridor-induced tourism behavior and offer evidence-based insights for designing effective tourism development strategies under the CPEC framework.

2. Conceptual Framework and Hypotheses Development

2.1. Theoretical Foundation

The conceptual framework of this study is primarily grounded in the Theory of Planned Behavior (TPB) and Random Utility Theory (RUT), which together provide complementary explanations for tourism travel willingness. According to the Theory of Planned Behavior, behavioral intention is influenced by attitudes toward the behavior, perceived behavioral control, and contextual constraints. In tourism contexts, attitudes reflect individuals' evaluations of expected travel experiences and therefore play an important role in shaping travel [2]. In the present study, attitudinal constructs such as perceived desirability, pleasantness, and comfort of traveling along CPEC represent evaluative judgments influencing individuals' willingness to undertake tourism trips.

Within the TPB framework, perceived behavioral control refers to individuals' perception of how easy or difficult it is to perform a behavior. In tourism travel decisions, knowledge-related variables such as awareness of tourism destinations, visa procedures, and accommodation arrangements reduce uncertainty and increase travelers' confidence in their ability to undertake tourism trips [17]. Therefore, tourism knowledge and awareness are conceptualized as indicators of perceived behavioral control influencing tourism willingness.

Complementing this perspective, Random Utility Theory explains travel decisions as outcomes of utility maximization under constraints. Individuals evaluate alternative travel options based on expected benefits and costs associated with each option. Sociodemographic characteristics such as income, gender, and travel experience influence available resources and mobility opportunities, thereby shaping the perceived feasibility of tourism participation. Similarly, infrastructure attributes and accessibility conditions influence perceived travel utility by affecting travel convenience, comfort, and accessibility [12–14,18].

Based on these theoretical considerations, the present study developed a conceptual framework linking four major constructs socio-demographic characteristics, attitudinal factors, tourism knowledge and awareness, and built environment attributes to tourism travel willingness (Figure 1). The framework further distinguishes between domestic tourism willingness within Pakistan and cross-border tourism willingness toward China in order to capture the differences in behavioral mechanisms between these two travel contexts.

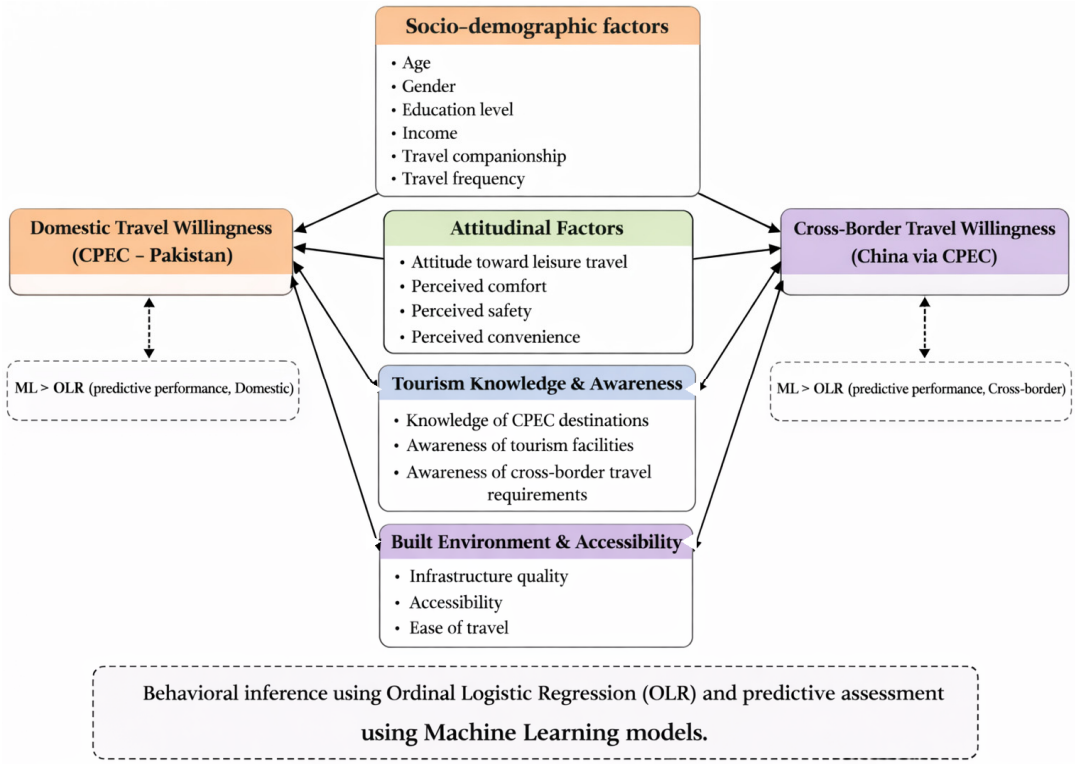


Figure 1. Conceptual framework of the study.

2.2. Socio-Demographic Characteristics

Socio-demographic characteristics have long been recognized as important determinants of tourism behavior. Variables such as gender, income, travel experience, and household composition influence tourism participation by shaping individuals' financial capacity, mobility resources, and travel preferences. Individuals with higher income and greater travel experience are generally more likely to undertake tourism trips because they possess greater economic resources and familiarity with travel environments [2,12].

From the perspective of Random Utility Theory, socio-demographic characteristics influence tourism decisions by shaping the perceived costs and benefits associated with tourism travel. Travelers with greater economic resources and prior travel experience may perceive tourism trips as more feasible and attractive compared with individuals facing stronger resource constraints [13,14,19].

Based on these considerations, the following hypotheses are proposed:

H1. *Socio-demographic characteristics significantly influence domestic tourism willingness along CPEC.*

H5. *Socio-demographic characteristics significantly influence cross-border tourism willingness towards China via CPEC.*

2.3. Attitudinal Factors

Attitudes toward travel experiences represent an important psychological determinant of tourism behavior. Travelers typically evaluate tourism opportunities based on expected enjoyment, comfort, and overall travel experience. Positive attitudes toward tourism activities increase individuals' likelihood of participating in discretionary travel activities [2,3].

According to the Theory of Planned Behavior, attitude reflects an individual's overall positive or negative evaluation of performing a behavior and serves as a key antecedent of behavioral intention. In the case of corridor tourism, positive evaluations of travel along

CPEC, especially with respect to its desirability, pleasantness, and comfort, may enhance individuals' willingness to engage in tourism trips.

Therefore, the following hypotheses are proposed:

H2. *Attitudinal factors positively influence domestic travel willingness along CPEC.*

H6. *Attitudinal factors positively influence cross-border travel willingness towards China via CPEC.*

2.4. Tourism Knowledge and Awareness

Tourism knowledge and awareness represent travelers' understanding of tourism destinations, travel procedures, and available tourism services. Knowledge reduces uncertainty and improves travelers' ability to plan tourism trips effectively [20].

Within the Theory of Planned Behavior, knowledge-related variables contribute to perceived behavioral control by reducing uncertainty and increasing travelers' confidence in their ability to undertake tourism travel. This factor may be particularly important in cross-border tourism contexts, where travelers must consider institutional procedures such as visa requirements and accommodation arrangements [9,21–23].

Based on these arguments, the following hypotheses are proposed:

H3. *Tourism knowledge and awareness positively influence domestic travel willingness along CPEC.*

H7. *Tourism knowledge and awareness exert a stronger influence on cross-border travel willingness towards China.*

2.5. Built Environment and Accessibility Attributes

Infrastructure quality and accessibility play an important role in shaping tourism travel decisions. Improved transportation infrastructure can enhance travel comfort, reduce travel time, and increase accessibility to tourism destinations [24–27].

From the perspective of Random Utility Theory, improvements in infrastructure increase the perceived utility of tourism travel by reducing travel costs and increasing travel convenience [28]. Consequently, positive perceptions of built environment conditions and accessibility along CPEC may increase travelers' willingness to undertake tourism trips.

H4. *Built environment and accessibility factors positively influence domestic travel willingness along CPEC.*

H8. *Built environment and accessibility factors positively influence cross-border travel willingness towards China via CPEC.*

2.6. Methodological Hypotheses: Econometric and Machine Learning Models

Travel willingness decisions involve complex interactions among socio-demographic characteristics, attitudinal factors, tourism knowledge, and built environment perceptions. Traditional econometric models such as ordinal logistic regression are widely used for analyzing ordered behavioral responses and are particularly valuable for behavioral interpretation and hypothesis testing. These models allow researchers to estimate the influence of explanatory variables on individuals' travel willingness while maintaining interpretability of model coefficients [15].

However, tourism travel decisions often involve non-linear relationships, interaction effects, and threshold-based behavioral responses that may not be fully captured by traditional econometric approaches. For example, the influence of tourism knowledge or

travel experience may only become significant after a certain threshold level is reached, and interactions between socio-demographic characteristics and infrastructure conditions may produce complex behavioral responses. Such patterns may be difficult to represent using linear or additive model structures [15].

In contrast, machine learning models provide greater flexibility in modeling complex behavioral relationships. These models can capture non-linear effects, interaction mechanisms, and hidden patterns within large behavioral datasets. In recent travel behavior studies, machine learning algorithms have demonstrated strong predictive performance in analyzing travel mode choice, technology adoption, and tourism participation behavior [14].

Recent research in transportation and tourism behavior indicates that machine learning models can outperform traditional discrete choice models when complex interactions among explanatory variables exist. By identifying non-linear decision rules and threshold effects, machine learning models can provide improved predictive accuracy in behavioral modeling contexts. In the context of CPEC tourism, travel willingness decisions may be influenced by multiple interacting constraints, including socio-demographic conditions, attitudinal perceptions, tourism knowledge, and infrastructure accessibility. Therefore, machine learning models are expected to capture these complex interactions more effectively than traditional econometric models when predicting tourism travel willingness.

Based on these considerations, the following methodological hypotheses are proposed:

H9. *Machine learning models outperform ordinal logistic regression in predicting domestic travel willingness.*

H10. *Machine learning models outperform ordinal logistic regression in predicting cross-border travel willingness.*

3. Materials and Methods

3.1. Research Design

This study adopted a quantitative cross-sectional research design based on a stated preference (SP) survey to examine tourism travel willingness in the context of the CPEC. SP approaches are widely used in travel behavior research when the objective is to examine behavioral intentions and preferences under hypothetical conditions rather than observed travel behavior [28,29].

The analytical framework integrates ordinal logistic regression (OLR) and machine learning (ML) models. Ordinal logistic regression is used to estimate the behavioral effects of explanatory variables and test the proposed hypotheses, while machine learning models are applied to capture potential non-linear relationships and interaction effects among explanatory variables. Separate models are estimated for domestic tourism willingness within Pakistan and cross-border tourism willingness toward China.

3.2. Questionnaire Design

The questionnaire was developed based on the literature on tourism behavior and travel decision making. A pre-survey questionnaire study was conducted to evaluate the clarity, internal consistency, and accuracy of the questionnaire items and to modify the questions based on Pakistani environment. For this purpose, a panel of professors from well-recognized universities and government officials from Pakistan Tourism Development Corporation (PTDC) were recruited and enquired about their opinion regarding tourism behavior in the country. Final questionnaire was devised based on their opinion in which

most of the items were from previous studies adjusted according to suit the Pakistani tourist [30–32].

Attitudinal constructs such as perceived desirability, pleasantness, and comfort of tourism travel were measured using five-point Likert-type scales ranging from 1 (strongly disagree) to 5 (strongly agree). Likert scales are widely used in behavioral and tourism research to capture subjective perceptions and psychological constructs influencing travel decisions [33]. Content validity of the questionnaire was ensured through expert review during the pre-survey stage, while internal consistency of attitudinal items was evaluated during the data screening process.

3.3. Sampling Strategy and Data Collection

The target population consisted of Pakistani residents with potential interest in tourism travel. The survey was distributed online through email and WhatsApp among members of the public and employees of various public and private sector organizations. Respondents were provided with a brief description of the research objectives and an overview of the CPEC initiative before completing the questionnaire. Informed consent for data usage was complementary before starting the questionnaire.

Because the questionnaire was distributed through online communication channels rather than through a predefined sampling frame, the study employed a non-probability convenience sampling approach, which is commonly used in tourism perception and behavioral intention studies [34].

The data collection period lasted six weeks, from the second week of January 2020 to the third week of February 2020. A total of 461 responses were received during the survey period.

3.4. Data Screening and Processing

Before the final dataset was prepared for analysis, several data screening procedures were applied to ensure the reliability and completeness of the survey responses. First, responses containing more than 10% missing values were removed from the dataset. Second, responses exhibiting straight-line answering patterns, where respondents selected identical responses for all survey items, were excluded as they indicated a lack of engagement with the questionnaire. Third, duplicate responses were identified and removed when identical answers were submitted within the same response period.

After applying these screening procedures, 20 responses were excluded, resulting in a final analytical dataset of 441 valid observations used in the econometric and machine learning analyses.

3.5. Analytical Framework

All statistical analyses were conducted using SPSS version 22.0, while machine learning analyses were performed using RapidMiner Studio version 10.3. To capture both behavioral interpretation and predictive performance, this study employed a dual analytical framework combining econometric modeling and machine learning approaches. OLR was used to estimate interpretable behavioral effects and test the proposed hypotheses, while ML models were used to explore complex behavioral patterns and potential non-linear relationships among explanatory variables [14–16].

Ordinal logistic regression (OLR) was used to analyze tourism travel willingness because the dependent variable represents ordered response categories [35–37]. The model assumes the existence of an underlying latent utility that governs observed ordinal responses through a series of threshold parameters [38]. To ensure model validity, several diagnostic tests were performed. The proportional odds (parallel lines) assumption was evaluated using likelihood-ratio and Wald tests [39]. Model robustness and stability were

further assessed using likelihood ratio tests, Pearson goodness-of-fit statistics, variance inflation factors (VIF), and Pearson's bivariate correlation analysis to identify potential multicollinearity among explanatory variables [40,41].

To complement the econometric analysis, several machine learning classifiers were implemented to evaluate predictive performance. Machine learning approaches are increasingly applied in travel behavior research because they are capable of identifying complex non-linear relationships and interaction effects within behavioral datasets [42,43]. The classifiers implemented were *naïve Bayes classifier; decision trees; ensemble models including random forest, bagging, and boosting; support vector machines, fast large margin classifiers; and neural networks.* These classifiers represent different modeling approaches including probabilistic learning, rule-based partitioning, ensemble prediction, margin-based classification, and non-linear neural learning. The use of multiple algorithms allows a comprehensive comparison between econometric and machine learning approaches for predicting tourism travel willingness [42,44–49]. Model performance was evaluated using accuracy, precision, recall, F-score, and receiver operating characteristic (ROC) curves. These indicators provide a comprehensive assessment of predictive performance and enable comparison across econometric and machine learning models [50,51].

Machine learning models were trained using a structured procedure incorporating data splitting, cross-validation, and hyperparameter tuning. The dataset was divided into training (70%) and testing (30%) subsets to evaluate out-of-sample predictive performance and reduce overfitting [14,46,52]. To improve model generalizability, 10-fold cross-validation was applied during training [47]. Model hyperparameters were optimized using a grid search approach, where multiple parameter combinations were evaluated and the optimal configuration was selected based on classification accuracy and F-score [53]. Key hyperparameters included tree depth and number of trees for ensemble models, learning rate for boosting algorithms, regularization and kernel parameters for support vector machines, and network architecture for neural networks. For models sensitive to variable scale, feature normalization was applied prior to training [54].

4. Analysis and Findings

4.1. Descriptive Statistics of Socio-Demographic Variables

Table 1 presents the socio-demographic characteristics of the respondents. The sample was male-dominated, with males accounting for 74.4% and females 25.6%. This imbalance is consistent with documented gender disparities in literacy and online survey participation in Pakistan [55]. Most respondents fell within the 18–25 years and 26–35 years age groups, indicating that the sample largely represents young adults who are typically more active users of online survey platforms. The sample was highly educated, with approximately 93% of respondents holding a bachelor's degree or higher. Most respondents were employed either full-time or part-time, while students accounted for 23.8% of the sample.

In terms of mobility resources, 57.8% of respondents reported holding a valid driving license, while about 68% reported owning at least one vehicle. The majority of respondents resided in urban areas (66.2%), followed by suburban (20.0%) and rural areas (13.8%). This distribution is consistent with the greater availability of internet access in urban areas of Pakistan [56]. Income levels were classified based on national per capita income thresholds [57]. Household income was concentrated in the middle-income category (46.5%), followed by high-income (28.8%) and low-income (24.7%) groups. Regarding travel experience, 44.2% of respondents reported low travel frequency in the past three years, while 35.6% reported average and 20.2% reported high travel frequency. Travel companionship was largely family-oriented. Nearly half of respondents (48.5%) reported that they would prefer

traveling with family members, followed by friends (29.0%), individual travel (13.4%), and tour groups (9.1%).

Table 1. Descriptive statistics of the socio-demographic variables.

Variable	Category	Valid Percentage (%)
Gender	Male	74.4
	Female	25.6
Age	18 to 25	34.9
	26 to 35	37.9
	36 to 45	11.3
	46 to 60	9.5
	Above 60	6.3
Education	S.S.C	0.5
	H.S.S.C	6.1
	Bachelor	56.2
	M.S/M.Phil	35.1
	PhD	2.0
Work status	Full time	55.8
	Part time	8.6
	Student	23.8
	Retired	1.8
	Unemployed	10.0
Driving license	Yes	57.8
	No	42.2
Household type	Couples without children	17.7
	Single parent	20.2
	Couples with children	35.6
	Single	26.5
Vehicle possession	0	32.4
	1	54.2
	2 or more	13.4
Residential neighborhood	Urban	66.2
	Suburban	20.0
	Rural	13.8
Household income	Low (less than 50 K)	24.7
	Average (50 K to 100 K)	46.5
	High (greater than 100 K)	28.8
Frequency of travel in last 3 years	Low (1 to 5 times)	44.2
	Average (5 to 10 times)	35.6
	High (greater than 10 times)	20.2
Travel companion	Family	48.5
	Friends	29.0
	Tour groups	9.1
	Individual	13.4

These descriptive characteristics provide an overview of the socio-economic background of respondents and help contextualize the behavioral results examined in the subsequent econometric models. Socio-demographic characteristics such as gender, income, and prior travel experience have been widely identified as important determinants of tourism participation and travel decision-making [58].

4.2. Descriptive Statistics of Domestic CPEC Travel Willingness

The results (Table 2) suggest that an overwhelming majority of Pakistani tourists (82.7%) agree or strongly agree to travelling the CPEC for tourism upon its completion. Most respondents' report agreement/strong agreement with willingness to travel after completion (mean ≈ 3.97) and similarly positive attitudinal evaluations for desirability, pleasantness, and comfort (means ≈ 3.89–4.01). These results suggest that, at the intention level, domestic CPEC tourism demand is already favorable and may be activated if travelers perceive the corridor as safe, pleasant, and comfortable.

Table 2. Descriptive statistics of domestic travel willingness.

Options	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Question 1	I am willing to travel CPEC for tourism after completion? (Mean 3.97)				
Frequency (%)	22 (5.0)	13 (2.9)	50 (11.3)	226 (51.2)	130 (29.5)
Question 2	I have knowledge about tourism along CPEC? (Mean 3.06)				
Frequency (%)	33 (7.5)	78 (17.7)	200 (45.4)	88 (20.0)	42 (9.5)
Question 3	CPEC tourism is desirable to me? (Mean 3.90)				
Frequency (%)	9 (2.0)	26 (5.9)	72 (16.3)	228 (51.7)	106 (24.0)
Question 4	CPEC tourism will be pleasant for me? (Mean 4.01)				
Frequency (%)	4 (0.9)	13 (2.9)	69 (15.6)	245 (55.6)	110 (24.9)
Question 5	I feel comfortable in traveling CPEC for tourism? (Mean 3.89)				
Frequency (%)	9 (2.0)	23 (5.2)	79 (17.9)	225 (51.0)	105 (23.8)
Question 6	You will be visiting CPEC for tourism with whom?				
Options	Family	Friends	Tour groups	Solo	
Frequency (%)	214 (48.5)	128 (29.0)	40 (9.1)	59 (13.4)	

The options for questions 1 to 5 are strongly disagree, disagree, neutral, agree, and strongly agree (from left to right). Percentage in parentheses.

4.3. Descriptive Statistics of Cross-Border Travel Willingness

The descriptive statistics of factors associated with willingness to travel China by CPEC are shown in Table 3. The majority (83%) of the responders were willing to travel for cross-border travel to China (mean ≈ 4.14). However, the descriptive statistics revealed important differences in knowledge levels. While general and destination knowledge were around 'average' (means ≈ 3.06 and 3.04), procedural knowledge was considerably weaker with visa/stay knowledge (mean ≈ 2.08) and hotel/accommodation knowledge (mean ≈ 2.27). This pattern suggests that while interest in cross-border tourism was high, practical and institutional constraints may limit actual travel behavior. Previous research has similarly found that lack of procedural knowledge and travel information can reduce international tourism participation [8,20].

4.4. Collinearity and Correlation Diagnostics

Before estimating the regression models, diagnostic tests were conducted to examine multicollinearity and relationships among explanatory variables. Tables 4 and 5 present the results of the likelihood ratio test and variance inflation factor (VIF) analysis. VIF should not be more than 10, otherwise it is indicative of multi-collinearity [41]. The VIF values for socio-demographic variables were relatively low, indicating no serious multicollinearity problems. For domestic tourism variables, VIF values ranged between approximately 1.06 and 3.16. Although attitudinal variables showed slightly higher values, this is expected because desirability, pleasantness, and comfort represent related dimensions of tourism experience.

Table 3. Descriptive statistics of cross-border travel willingness.

Question 1	After the completion of CPEC I would like to travel to China for tourism? (Mean 4.14)				
Frequency (%)	13 (2.9)	16 (3.6)	46 (10.4)	188 (42.6)	178 (40.4)
Question 2	How much do you know about tourism along CPEC? (Mean 3.06)				
Frequency (%)	33 (7.5)	78 (17.7)	200 (45.4)	88 (20.0)	42 (9.5)
Question 3	How much do you know about tourist destinations along CPEC? (Mean 3.04)				
Frequency (%)	34 (7.7)	90 (20.4)	190 (43.1)	80 (18.1)	47 (10.7)
Question 4	How much do you know about visa/stay period for visiting China via CPEC? (Mean 2.08)				
Frequency (%)	169 (38.3)	117 (26.5)	118 (26.8)	23 (5.2)	14 (3.2)
Question 5	How much do you know about hotel booking procedures and accommodations for tourism to China? (Mean 2.27)				
Frequency (%)	154 (34.9)	117 (26.5)	107 (24.3)	23 (5.2)	40 (9.1)
Question 6	You will be visiting CPEC for tourism with whom?				
Options	Family	Friends	Tour groups	Individual/Alone	
Frequency (%)	214 (48.5)	128 (29.0)	40 (9.1)	59 (13.4)	

The options for questions 1 to 5 are not at all, below average, average, above average, and very much (from left to right). Percentages in parentheses.

Table 4. Likelihood ratio and collinearity diagnosis *of domestic* CPEC tourism.

Variables	Chi-Square	VIF
General knowledge of CPEC	5.234	1.303
Desirability of CPEC tourism	2.410	2.563
Pleasantness of CPEC tourism	5.431	3.160
Comfort in travelling CPEC	4.938	2.707
Travel companion	4.057	1.067
Gender	3.907	1.065
Net income	7.165	1.146
Frequency of travel	3.841	1.187

Table 5. Likelihood ratio and collinearity diagnosis of China tourism variables.

Variables	Chi-Square	VIF
General knowledge of CPEC	15.798	6.444
Desirability of CPEC tourism	4.693	6.554
Pleasantness of CPEC tourism	2.122	2.845
Comfort in travelling CPEC	5.105	2.873
Travel companion	5.548	1.031
Gender	4.107	1.085
Net income	6.165	1.133
Frequency of travel	3.841	1.187

For cross-border tourism variables, general knowledge and destination knowledge showed higher VIF values, reflecting the close association between knowledge-related variables in international tourism contexts.

Pearson's bivariate correlation results (Tables 6 and 7) further confirm these relationships. In the domestic model, knowledge was positively correlated with desirability, pleasantness, and comfort, while attitudinal variables were strongly interrelated. In the cross-border model, knowledge variables exhibited even stronger correlations, indicating that different forms of tourism knowledge were closely linked in shaping international travel willingness.

Table 6. Pearson's correlation among variables used in the OLR model for CPEC tourism (Domestic tourism).

	1	2	3	4	5	6	7	8
General knowledge	1							
Desirability	0.389 **	1						
Pleasantness	0.389 **	0.754 **	1					
Comfort	0.408 **	0.696 **	0.764 **	1				
Travel companion	−0.033	−0.103 *	−0.127 **	−0.102 *	1			
Gender	−0.163 **	−0.181 **	−0.192 **	−0.215 **	−0.013	1		
Net income	0.136 **	0.037	0.071	0.034	−0.183 **	−0.026	1	
Frequency of travel	0.233 **	0.086	0.121 *	0.138 **	−0.163 **	−0.107 *	0.318 **	1

* Correlation is significant at the 0.05 level (1-tailed); ** correlation is significant at the 0.01 level (2-tailed).

Table 7. Pearson's correlation among variables used in OLR model for CPEC tourism (cross-border tourism).

	1	2	3	4	5	6	7	8
General knowledge	1							
Desirability	0.917 **	1						
Pleasantness	0.482 **	0.484 **	1					
Comfort	0.458 **	0.477 **	0.792 **	1				
Travel companion	−0.080	−0.074	−0.100 *	−0.087	1			
Gender	−0.163 **	−0.143 **	−0.012	−0.069	0.136 **	1		
Net income	0.136 **	0.127 **	0.144 **	0.15 **	0.000	−0.026	1	
Frequency of travel	0.233 **	0.252 **	0.130 **	0.082	−0.001	−0.107 *	0.318 **	1

* Correlation is significant at the 0.05 level (1-tailed); ** correlation is significant at the 0.01 level (2-tailed).

4.5. Ordinal Logistic Regression Models

4.5.1. Domestic Tourism Willingness

Two ordinal logistic regression models were estimated to examine tourism willingness in domestic and cross-border contexts. For domestic tourism along the CPEC, the model demonstrated strong overall fit, with a likelihood ratio chi-square of 445.211 ($p < 0.01$) and a Pearson goodness-of-fit value of 0.999. The proportional odds assumption was also satisfied [37–39].

The results in Table 8 show that several socio-demographic and attitudinal variables significantly influenced domestic tourism willingness. Among socio-demographic variables, gender, travel frequency, net income, and travel companionship were significant. Male respondents were more likely to report stronger willingness than female respondents, a pattern that reflects broader socio-cultural constraints on female mobility in Pakistan [59–64]. Respondents with lower travel frequency were less willing to travel along the CPEC, indicating that prior travel experience increases openness toward corridor tourism [65,66]. Similarly, lower-income respondents showed lower willingness, suggesting that financial capacity remains an important condition for discretionary tourism participation [67–70]. Travel companionship has one of the strongest effects in the domestic model. Relative to individual travel, respondents planning to travel with family, friends, or tour groups were substantially more willing to undertake domestic CPEC tourism. These findings suggests that domestic corridor tourism is strongly shaped by social travel preferences, which is in line with previous research; thus, the socio-demographic results support H1.

Attitudinal factors emerged as the most powerful determinants of domestic travel willingness. Consistent with previous research, lower levels of desirability, pleasantness, and comfort are consistently associated with lower odds of expressing strong willingness to

travel [30–32,71–78]. These findings indicate that domestic tourism willingness is primarily attitude-driven, with experiential perceptions playing a central role, thus supporting H2.

Table 8. Results of the OLR model for willingness to travel the CPEC for domestic tourism.

Variable	Category	B	SE	Wald	OR
Gender	Male	0.590 *	0.263	5.029	1.803
Frequency of travel	Low	−0.502	0.330	2.311	0.605
	Average	−0.833 **	0.330	6.389	0.434
	High		Ref		
Net income	Low	−0.683 *	0.332	4.233	0.505
	Average	−0.437	0.282	2.414	0.646
	High		Ref		
Travel companion	Family	0.761 *	0.360	4.484	2.140
	Friends	0.969 **	0.383	6.392	2.635
	Tour groups	1.274 **	0.491	6.718	3.575
	Individual		Ref		
General knowledge	Not at all	−1.622 **	0.641	6.413	0.197
	Below average	−0.355	0.491	0.524	0.701
	Average	0.061	0.441	0.019	1.062
	Above average	−0.149	0.469	0.101	0.861
	Very much		Ref		
Desirability of CPEC tourism	Strongly disagree	−2.686 **	1.141	5.539	0.068
	Disagree	−3.752 **	0.700	28.723	0.023
	Neutral	−3.014 **	0.521	33.52	0.049
	Agree	−1.046 **	0.347	9.106	0.351
	Strongly agree		Ref		
Pleasantness of CPEC tourism	Strongly disagree	−5.678 **	1.906	8.873	0.003
	Disagree	−3.713 **	0.919	16.318	0.024
	Neutral	−2.443 **	0.568	18.518	0.086
	Agree	−1.181 **	0.376	9.843	0.306
	Strongly agree		Ref		
Comfort in travelling the CPEC	Strongly disagree	−4.434 **	1.261	12.359	0.011
	Disagree	−2.240 **	0.705	10.104	0.106
	Neutral	−1.716 **	0.497	11.939	0.179
	Agree	−0.737 *	0.359	4.212	0.478
	Strongly agree		Ref		

OR = odds ratios. * >95% level of significance. ** >99% level of significance.

By contrast, tourism knowledge showed a more limited direct effect. Only the lowest level of general knowledge was significant, indicating that minimal awareness is necessary, but beyond that, knowledge does not directly increase willingness proportionally, consistent with prior research linking knowledge to perception and risk evaluation [79–83]. Therefore, H3 is satisfied.

Built environment variables did not show a strong direct effect in the final domestic model, leading to the rejection of H4.

Taken together, the domestic results suggest that CPEC tourism willingness within Pakistan is primarily shaped by attitudinal evaluations and social travel preferences, while socio-demographic characteristics influence the feasibility of participation.

4.5.2. Cross-Border Tourism Willingness

For cross-border tourism to China, the OLR model also showed satisfactory fit, with a likelihood ratio chi-square of 76.828 ($p < 0.01$) and a Pearson goodness-of-fit value of 0.359.

The proportional odds assumption was satisfied, indicating stable coefficient estimates across response thresholds.

Table 9 shows that cross-border tourism willingness was influenced more strongly by knowledge-related and feasibility-related variables than by attitudinal variables. Gender remained significant, with male respondents showing stronger willingness. Travel frequency was also significant, suggesting that more experienced travelers were more willing to undertake cross-border tourism. The role of income differed from the domestic model. The low-income category was positive and significant relative to high income, which may reflect higher aspirational willingness among younger or student respondents despite lower economic capacity. Therefore, socio-demographics influence cross-border travel, thus supporting H5.

Table 9. Results of the OLR model for willingness to travel the CPEC for cross-border tourism.

Variable	Category	B	SE	Wald	OR
Gender	Male	0.456 *	0.220	4.305	1.577
Frequency of travel	Low	−0.70 **	0.280	6.233	0.496
	Average	−0.629 *	0.281	5.01	0.533
	High		Ref		
Net income	Low	0.544 *	0.275	3.92	1.72
	Average	0.351	0.236	2.21	1.42
	High		Ref		
General knowledge	Not at all	−4.89 **	1.18	16.99	0.007
	Below average	−3.61 **	0.939	15.424	0.026
	Average	−2.31 **	0.775	8.872	0.099
	Above average	−2.03 **	0.818	6.081	0.131
	Very much		Ref		
Destination knowledge	Not at all	3.13 **	1.152	7.380	22.87
	Below average	2.12 **	0.869	5.936	8.31
	Average	1.26	0.727	2.986	3.511
	Above average	1.501 *	0.780	3.701	4.486
	Very much		Ref		
Hotel and accommodation knowledge	Not at all	−2.29 **	0.898	6.507	0.101
	Below average	−1.76 *	0.881	3.998	0.171
	Average	−1.63 *	0.866	3.558	0.195
	Above average	−1.82 *	0.883	4.257	0.162
	Very much		Ref		
Visa and stay knowledge	Not at all	1.071 *	0.539	3.943	2.918
	Below average	0.231	0.519	0.198	1.259
	Average	−0.048	0.488	0.009	0.953
	Above average	−0.085	0.546	0.024	0.918
	Very much		Ref		
Willingness enhancement factors	Infrastructure	0.467 *	0.235	3.935	1.597
	Info & marketing	0.262	0.251	1.089	1.299
	Safety & security		Ref		

OR = odds ratios. * >95% level of significance. ** >99% level of significance.

Attitudinal variables were tested but were not statistically significant in the final cross-border specification. This indicates that, unlike domestic tourism, cross-border travel willingness was less influenced by experiential attitudes and more constrained by knowledge, procedures, and institutional barriers; thus, H6 was not supported.

Knowledge variables played a central role in the cross-border model supporting H7. Lower levels of general knowledge were associated with very low odds of stronger

willingness, indicating that basic awareness is a prerequisite for cross-border tourism. Similarly, weaker hotel and accommodation knowledge significantly reduced willingness, highlighting the importance of procedural feasibility. Destination knowledge also showed a positive contribution, suggesting that familiarity with tourism opportunities improves travel intention.

The model also showed that respondents who identified infrastructure as a key willingness-enhancing factor were more likely to report stronger cross-border willingness than those primarily concerned with safety and security. This result aligns with previous studies suggesting safety/security as the dominant concern overall [82,84]. This suggests that international corridor tourism is particularly sensitive to perceived feasibility and enabling conditions; therefore, built environment factors impact willingness, thus supporting H8.

Overall, the cross-border results in line with previous studies indicate that tourism willingness toward China is mainly shaped by knowledge, procedural awareness, and feasibility constraints, rather than by attitudinal evaluations alone [85].

4.6. Machine Learning Models

The performance comparison between machine learning models and logistic regression for domestic tourism willingness is presented in Table 10. The results show that machine learning classifiers consistently outperformed the regression benchmark in predictive accuracy.

Table 10. Performance measures of ML and LR models for domestic willingness.

Models	Accuracy	Precision	Recall	F-Score
Naïve Bayes	89.7	95.0	91.9	93.3
Generalized linear model	89.6	91.5	95.9	93.6
Fast large margin	93.6	94.0	98.0	96.0
Deep learning	86.4	93.0	89.7	91.1
Decision tree	87.4	90.1	93.7	91.7
Random forest	92.0	94.0	95.9	94.9
Gradient boosted trees	92.9	92.5	99.0	95.6
Support vector machine	92.8	94.1	97.0	95.4
Logistic regression	81.0	83.8	92.6	87.9

For Pakistani willingness, classification accuracy ranged from 86.4% to 93.6% across machine learning models. The best-performing classifiers were fast large margin (93.6%), gradient boosted trees (92.9%), support vector machine (92.8%), and random forest (92.0%). These models also achieved strong F-scores, indicating robust predictive performance. In contrast, logistic regression achieved an accuracy of 81.0% and a lower F-score than the best-performing ML classifiers [50,51,86]. This confirms that ML models provide superior predictive capability for domestic tourism willingness. These findings support H9, indicating that ML models outperformed OLR in predicting domestic travel willingness.

Table 11 presents the model performance for cross-border tourism willingness toward China. Compared with domestic tourism, predictive accuracy was lower and more tightly clustered, ranging from approximately 79% to 81%, which reflects the greater complexity of cross-border travel decisions [82]. Among the machine learning models, support vector machine (81.1%) and fast large margin (81.0%) provided the best overall performance. Random forest also performed well, particularly in terms of recall. Naïve Bayes and logistic regression achieved very high recall values, but this appeared to come at the cost of lower balance between true positives and false positives.

Table 11. Performance measures of ML and OLR models for China willingness.

Models	Accuracy	Precision	Recall	F-Score
Naïve Bayes	79.4	79.4	100	88.4
Generalized linear model	79.5	84.4	91.4	87.4
Fast large margin	81.0	86.7	90.4	88.3
Deep learning	79.4	80.6	98.1	88.3
Decision tree	80.3	88.7	86.1	87.2
Random forest	80.4	81.3	98.2	88.7
Gradient boosted trees	79.5	85.4	89.0	87.0
Support vector machine	81.1	85.8	91.4	88.3
Logistic regression	79.4	79.4	100	88.4

Overall, the machine learning models again showed a predictive advantage over the regression benchmark, although the improvement was more modest than in the domestic case. These findings support H10, indicating that machine learning models also outperform ordinal logistic regression in predicting cross-border travel willingness.

Receiver Operator Characteristics (ROC) Curves

Figures 2 and 3 present the ROC curves for domestic and cross-border tourism willingness. ROC curves plot the true positive rate against the false positive rate across different classification thresholds, while the area under the curve (AUC) summarizes discriminatory power. Curves that bow strongly toward the upper-left corner indicate strong discriminatory power [50].

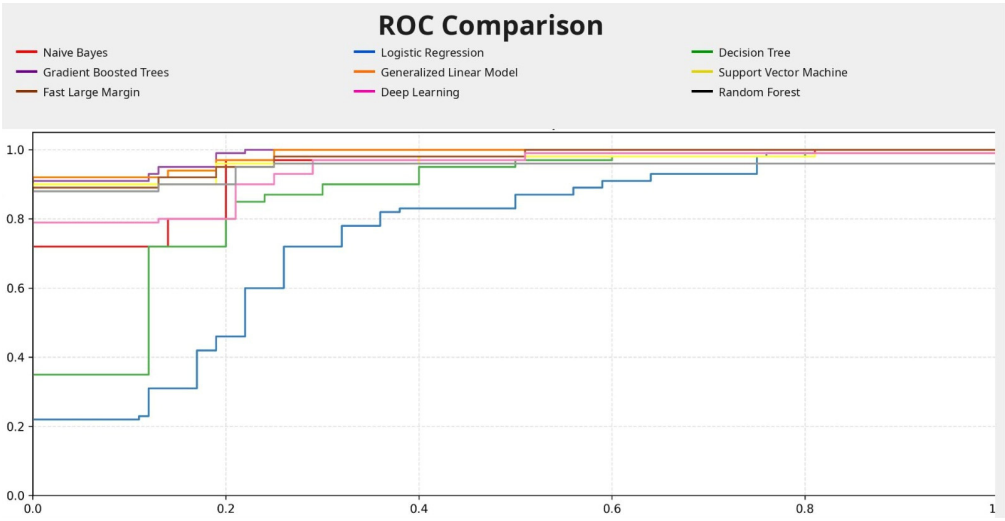


Figure 2. ROC curves for domestic willingness.

For domestic tourism willingness, the ROC curves lie well above the diagonal reference line, indicating strong and stable discriminatory performance across models. This suggests that domestic willingness is explained by observable behavioral and experiential attributes that allow clear separation between higher- and lower-willingness respondents [51,86].

For cross-border tourism willingness, the ROC curves displayed greater dispersion across models. This pattern reflects the more complex and constraint-sensitive nature of cross-border travel decisions. The wider variation across classifiers suggests that cross-border willingness is shaped by more non-linear and threshold-based mechanisms, which machine learning models are better able to detect.

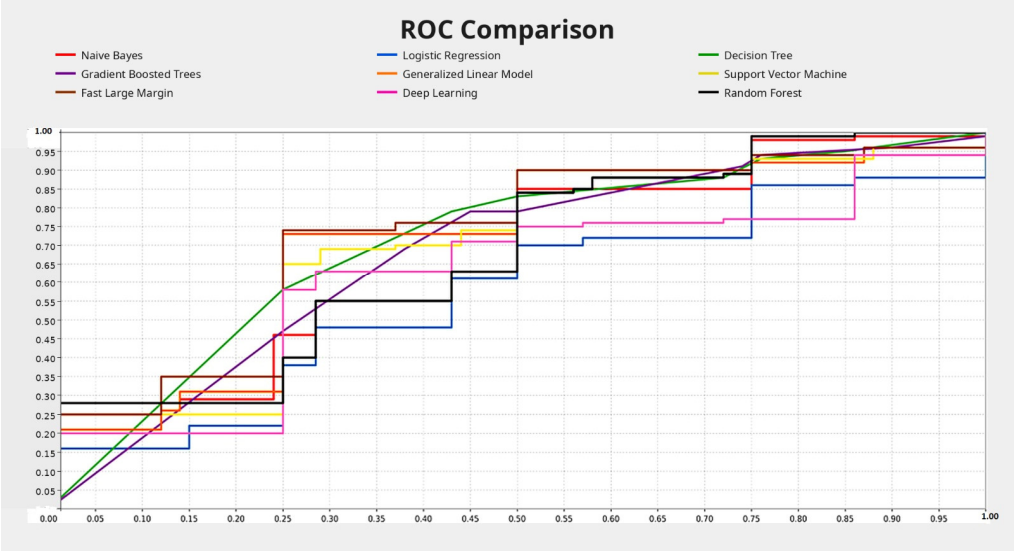


Figure 3. ROC curves for China willingness.

Taken together, the ROC results reinforce the conclusion that machine learning models provide stronger predictive performance, particularly where tourism willingness is shaped by complex behavioral constraints.

5. Discussion

Taken together, the findings suggest that domestic travel willingness along the CPEC follows a two-stage behavioral process. Socio-demographic capacity and prior travel experience establish the feasibility of travel, while attitudinal evaluations determine the intensity of willingness. Higher income, frequent travel experience, and group-based travel reduce cognitive and uncertainty costs, reflecting habitual and experience-driven decision making [58,87,88]. At the same time, positive perceptions of desirability, comfort, and pleasantness activate willingness once feasibility conditions are satisfied [18,85,89–92]. These results are consistent with the TPB, where attitudes influence behavioral intention when perceived behavioral control is sufficient [93]. This also aligns with RUT, which explains travel decisions as outcomes of utility maximization in which experiential attributes contribute to the perceived utility of travel alternatives [94]. From a policy perspective, the findings imply that infrastructure provision alone is insufficient to stimulate domestic tourism demand. Instead, CPEC tourism strategies should combine connectivity improvements with measures that enhance subjective travel experiences, including safety assurance, service quality, and destination attractiveness.

The OLR results for cross-border tourism highlight the greater importance of knowledge-related and institutional factors. Subjective knowledge about visa procedures, accommodation arrangements, and tourism infrastructure shows strong associations with willingness to travel, while perceived safety also emerges as a key determinant. These findings indicate that cross-border travel decisions are more cognitively demanding and sensitive to informational constraints than domestic travel decisions [24,95]. While socio-demographic variables remain relevant, their influence is comparatively weaker, suggesting that institutional and informational barriers play a dominant role in shaping cross-border willingness. Consequently, policies promoting cross-border tourism should focus on reducing perceived risk and uncertainty while improving procedural accessibility and travel information.

The comparative modeling results provide additional insights into the behavioral mechanisms underlying tourism willingness. The strong performance of ensemble and

margin-based machine learning models suggests that domestic tourism decisions are governed by non-linear and interaction-driven mechanisms that are not fully captured by traditional linear models but are effectively identified by these classifiers [42,96]. For example, income may influence willingness only beyond certain thresholds of travel frequency, while group travel preferences may amplify motivational effects for particular socio-demographic segments. Such interaction structures are naturally captured by machine learning models but may remain undetected in conventional econometric specifications.

A similar pattern is observed in the cross-border tourism context. The superior predictive performance of machine learning models suggests that knowledge-related and institutional constraints operate through threshold mechanisms. Variables such as awareness of visa requirements, perceived infrastructure quality, and safety perceptions may influence willingness only after a minimum level of awareness or perceived security is achieved [20,21]. These threshold effects violate the linearity and additivity assumptions of traditional econometric models but can be effectively modeled using flexible machine learning algorithms capable of capturing complex interactions and non-linear relationships [42].

From an applied perspective, the strong ROC performance observed in the domestic tourism models indicates that predicted willingness scores could be used for market segmentation. For example, tourism promotion policies could initially focus on travelers with high predicted willingness before expanding outreach strategies to broader population segments [91]. In contrast, the ROC patterns observed in the cross-border tourism models exhibited greater variation across classifiers, reflecting the additional complexity associated with international travel decisions. Institutional and informational barriers such as limited knowledge of visa procedures, uncertainty about accommodation arrangements, and perceived safety concerns can generate threshold effects in willingness formation. Once a minimum level of knowledge or confidence is achieved, willingness may increase sharply, producing non-linear behavioral patterns that are better captured by machine learning models than by traditional regression approaches [50]. From a policy perspective, lower or more variable ROC performance in the cross-border context should not necessarily be interpreted as model weakness. Instead, it may indicate that travel willingness is governed by a small number of binding constraints that are difficult to measure precisely within a single survey instrument [97]. ROC indicators therefore help distinguish between genuine model limitations and the behavioral complexity inherent in cross-border tourism decisions.

6. Conclusions and Suggestions

This study examined how the CPEC influences tourism travel willingness by distinguishing between domestic tourism within Pakistan and cross-border tourism toward China. The findings demonstrate that tourism willingness in corridor contexts is not behaviorally uniform but governed by distinct decision mechanisms.

For domestic tourism, willingness is primarily attitude-driven. Perceptions of desirability, pleasantness, and comfort emerge as the strongest determinants of travel intention. Socio-demographic characteristics and prior travel experience establish the feasibility of travel, while experiential evaluations determine the intensity of willingness. Infrastructure improvements therefore influence domestic tourism mainly through their impact on perceived comfort and overall travel experience rather than through direct structural effects.

In contrast, cross-border tourism willingness is constraint-sensitive and feasibility-screened. Knowledge-related variables, procedural awareness, and perceptions of infrastructure and safety conditions play a more prominent role in shaping willingness. This indicates that cross-border tourism decisions involve greater perceived uncertainty and require stronger informational support and institutional facilitation than domestic travel decisions.

From a methodological perspective, this study demonstrates the benefits of integrating ordinal logistic regression with machine learning models. Econometric models provide interpretable estimates of behavioral relationships, while machine learning models capture complex interactions and non-linear decision patterns. The results show that machine learning classifiers provide superior predictive performance, particularly in contexts where tourism decisions involve threshold effects and interaction-driven behavior.

From a policy perspective, the findings suggest that infrastructure provision alone may not be sufficient to stimulate tourism demand along economic corridors. Effective CPEC tourism strategies should therefore differentiate between domestic and cross-border tourism contexts. For domestic tourism, policy efforts should focus on enhancing travel experiences through improved service quality, safety, and destination attractiveness. For cross-border tourism, priority should be given to reducing informational barriers by improving visa transparency, tourism information platforms, and cross-border travel facilitation measures.

Despite these contributions, this study relied on stated preference data and a convenience sample, which may limit the generalizability of the findings. Future research could use larger datasets and revealed travel behavior to further examine corridor-induced tourism dynamics.

Author Contributions: Conceptualization, Y.A. and J.S.; methodology, Y.A. and M.H.; software, Y.A.; validation, Y.A. and M.H.; formal analysis, Y.A.; investigation, Y.A.; resources, J.S.; data curation, Y.A.; writing—original draft preparation, Y.A.; writing—review and editing, J.S. and M.H.; visualization, Y.A.; supervision, J.S.; project administration, J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China [grant number: 51578319, 51778340].

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (Ethics Committee) of COMSATS University Islamabad, Pakistan (IRB/CUI/19081, 7 January 2020).

Informed Consent Statement: Informed consent was obtained from all participants involved in the study.

Data Availability Statement: The original data presented in the study are openly available in Zenodo: https://doi.org/10.5281/zenodo.18860304.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AUC	Area Under the Curve
CPEC	China Pakistan Economic Corridor
LRT	Likelihood Ratio Test
ML	Machine Learning
NB	Naïve Bayes
OLR	Ordinal Logistic Regression
ROC	Receiver Operator Curves
SP	Stated Preference
SVM	Support Vector Machines
VIF	Variance Inflation Factor
WEF	Willingness Enhancement Factors

References

1. Ali, Y.; Shi, J.; Hussain, M. Mode Choice and Cross Border Tourism via China Pakistan Economic Corridor: Attitudes, Socio-Demographics, and Policy Implications. *J. China Tour. Res.* **2025**, *21*, 961–989. [CrossRef]
2. Banister, D.; Berechman, J. *Transport Investment and Economic Development*; Routledge: London, UK, 2003.
3. Ewing, R.; Cervero, R. Travel and the Built Environment. *J. Am. Plan. Assoc.* **2010**, *76*, 265–294. [CrossRef]
4. Khan, S.; Liu, G. The China–Pakistan Economic Corridor (CPEC): Challenges and prospects. *Area Dev. Policy* **2019**, *4*, 466–473. [CrossRef]
5. Ali, L.; Mi, J.; Shah, M.; Khan, A.; Imran, M. Transport culture akin to the China-Pakistan economic corridor. *Hum. Syst. Manag.* **2017**, *36*, 381–396. [CrossRef]
6. Sun, Y.; Ghani, U.; Pitafi, A.H.; Islam, T. CPEC Social-cultural impacts of China-Pakistan Economic Corridor on the well-being of local community. *J. Transp. Land Use* **2020**, *13*, 605–624. [CrossRef]
7. Lehto, X.Y.; O'Leary, J.T.; Morrison, A.M. The effect of prior experience on vacation behavior. *Ann. Tour. Res.* **2004**, *31*, 801–818. [CrossRef]
8. Han, H.; Hsu, L.-T.; Lee, J.-S. Empirical investigation of the roles of attitudes toward green behaviors, overall image, gender, and age in hotel customers' eco-friendly decision-making process. *Int. J. Hosp. Manag.* **2009**, *28*, 519–528. [CrossRef]
9. Han, H.; Lee, S.; Lee, C.-K. Extending the Theory of Planned Behavior: Visa Exemptions and the Traveller Decision-making Process. *Tour. Geogr.* **2011**, *13*, 45–74. [CrossRef]
10. George, R. Tourist's perceptions of safety and security while visiting Cape Town. *Tour. Manag.* **2003**, *24*, 575–585. [CrossRef]
11. Awais-E.-Yazdan, M.; Popescu, V.; Birau, R.; Bărbăcioru, I.C. Enhancing Tourist's Perceived Safety and Their Behavioral Intention in Thailand: A Pathway to Sustainable Tourism and Sustainable Economic Growth. *Sustainability* **2025**, *17*, 4297. [CrossRef]
12. Glimm, F.; Fabus, M. Determinants of the Willingness to Use Autonomous Mobility as a Service in Germany. *Future Transp.* **2004**, *4*, 746–764. [CrossRef]
13. Triantafillidi, E.; Tzouras, P.G.; Spyropoulou, I.; Kepaptsoglou, K. Identification of Contributory Factors That Affect the Willingness to Use Shared Autonomous Vehicles. *Future Transp.* **2023**, *3*, 970–985. [CrossRef]
14. Mullainathan, S.; Spiess, J. Machine Learning: An Applied Econometric Approach. *J. Econ. Perspect.* **2017**, *31*, 87–106. [CrossRef]
15. Ben-Akiva, M.; Mcfadden, D.; Train, K.; Walker, J.; Bhat, C.; Bierlaire, M.; Bolduc, D.; Boersch-Supan, A.; Brownstone, D.; Bunch, D.S.; et al. Hybrid Choice Models: Progress and Challenges. *Mark. Lett.* **2002**, *13*, 163–175. [CrossRef]
16. Athey, S.; Imbens, G.W. Machine Learning Methods That Economists Should Know About. *Annu. Rev. Econ.* **2019**, *11*, 685–725. [CrossRef]
17. Cheng, L.; Lai, X.; Chen, X.; De Vos, J.; Witlox, F. Applying a random forest method approach to model travel mode choice behavior. *Travel Behav. Soc.* **2019**, *14*, 1–10. [CrossRef]
18. Banister, D.; Berechman, Y. Transport investment and the promotion of economic growth. *J. Transp. Geogr.* **2001**, *9*, 209–218. [CrossRef]
19. Dijkhuijs, T.; Israel, F.; van Lierop, D. To Share or to Own? Understanding the Willingness to Adopt Shared and Owned Electric Automated Vehicles on Three Continents. *Future Transp.* **2023**, *3*, 1108–1123. [CrossRef]
20. Reisinger, Y.; Mavondo, F. Travel Anxiety and Intentions to Travel Internationally: Implications of Travel Risk Perception. *J. Travel Res.* **2005**, *43*, 212–225. [CrossRef]
21. Karatsoli, M.; Nathanail, E. University Commuters' Travel Behavior and Route Switching Under Travel Information: Evidence from GPS and Self-Reported Data. *Future Transp.* **2026**, *6*, 14. [CrossRef]
22. Juma, C.; Douglas, A. Visa requirements and visit intention: Applying the theory of planned behavior. *J. Policy Res. Tour. Leis. Events* **2023**, *17*, 780–801. [CrossRef]
23. Song, H.; Gartner, W.C.; Tasci, A.D.A. Visa restrictions and their adverse economic and marketing implications—Evidence from China. *Tour. Manag.* **2012**, *33*, 397–412. [CrossRef]
24. Neumayer, E. Visa Restrictions and Bilateral Travel. *Prof. Geogr.* **2010**, *62*, 171–181. [CrossRef]
25. Bautista-Hernández, D.A. Mode choice in commuting and the built environment in México City. Is there a chance for non-motorized travel? *J. Transp. Geogr.* **2021**, *92*, 103024. [CrossRef]
26. Park, K.; Ewing, R.; Scheer, B.C.; Tian, G. The impacts of built environment characteristics of rail station areas on household travel behavior. *Cities* **2018**, *74*, 277–283. [CrossRef]
27. Ye, R.; Titheridge, H. Satisfaction with the commute: The role of travel mode choice, built environment and attitudes. *Transp. Res. Part D Transp. Environ.* **2017**, *52*, 535–547.
28. Ben-Akiva, M.E.; Lerman, S.R. *Discrete Choice Analysis: Theory and Application to Travel Demand*; MIT Press: Cambridge, MA, USA, 1985.
29. Hensher, D.A. Stated preference analysis of travel choices: The state of practice. *Transportation* **1994**, *21*, 107–133. [CrossRef]
30. Anable, J.; Gatersleben, B. All work and no play? The role of instrumental and affective factors in work and leisure journeys by different travel modes. *Transp. Res. Part A Policy Pract.* **2005**, *39*, 163–181.

31. Molin, E.; Mokhtarian, P.; Kroesen, M. Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transp. Res. Part A Policy Pract.* **2016**, *83*, 14–29. [CrossRef]
32. Kroesen, M.; Chorus, C. The role of general and specific attitudes in predicting travel behavior—A fatal dilemma? *Travel Behav. Soc.* **2018**, *10*, 33–41. [CrossRef]
33. De Vos, J. Do people travel with their preferred travel mode? Analysing the extent of travel mode dissonance and its effect on travel satisfaction. *Transp. Res. Part A Policy Pract.* **2018**, *117*, 261–274.
34. Ilker, E.; Sulaiman Abubakar, M.; Rukayya Sunusi, A. Comparison of Convenience Sampling and Purposive Sampling. *Am. J. Theor. Appl. Stat.* **2015**, *5*, 1–4.
35. McCullagh, P. Regression Models for Ordinal Data. *J. R. Stat. Soc. Ser. B (Methodol.)* **2018**, *42*, 109–127. [CrossRef]
36. Greene, W.; Hensher, D. *Modeling Ordered Choices: A Primer*; Cambridge University Press: Cambridge, UK, 2009.
37. David, S.L.; Hosmer, W. *Applied Logistic Regression*, 2nd ed.; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2000.
38. Fullerton, A.S.; Xu, J. The proportional odds with partial proportionality constraints model for ordinal response variables. *Soc. Sci. Res.* **2012**, *41*, 182–198. [CrossRef]
39. Agresti, A. *Categorical Data Analysis*, 2nd ed.; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2002.
40. Washington, S.; Karlaftis, M.G.; Mannering, F.; Anastasopoulos, P. *Statistical and Econometric Methods for Transportation Data Analysis*, 2nd ed.; CRC Press: Boca Raton, FL, USA, 2011.
41. Allison, P. When Can You Safely Ignore Multicollinearity? 2012. Available online: https://statisticalhorizons.com/multicollinearity/ (accessed on 23 April 2024).
42. Hagenauer, J.; Helbich, M. A comparative study of machine learning classifiers for modeling travel mode choice. *Expert Syst. Appl.* **2017**, *78*, 273–282. [CrossRef]
43. Wang, S.; Mo, B.; Hess, S.; Zhao, J. Comparing hundreds of machine learning classifiers and discrete choice models in predicting travel behavior: An empirical benchmark. *arXiv* **2021**, arXiv:2102.01130.
44. Rish, I. An Empirical Study of the Naive Bayes Classifier. In Proceedings of the IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence, Seattle, WA, USA, 4 August 2001; pp. 41–46. Available online: https://faculty.cc.gatech.edu/ isbell/reading/papers/Rish.pdf (accessed on 23 April 2024).
45. Domingos, P.; Pazzani, M. On the Optimality of the Simple Bayesian Classifier under Zero-One Loss. *Mach. Learn.* **1997**, *29*, 103–130. [CrossRef]
46. Tamim Kashifi, M.; Jamal, A.; Samim Kashefi, M.; Almoshaogeh, M.; Masiur Rahman, S. Predicting the travel mode choice with interpretable machine learning techniques: A comparative study. *Travel Behav. Soc.* **2022**, *29*, 279–296. [CrossRef]
47. Zhao, X.; Yan, X.; Yu, A.; Van Hentenryck, P. Prediction and behavioral analysis of travel mode choice: A comparison of machine learning and logit models. *Travel Behav. Soc.* **2020**, *20*, 22–35. [CrossRef]
48. Cortes, C.; Vapnik, V. Support-vector networks. *Mach. Learn.* **1995**, *20*, 273–297. [CrossRef]
49. Shaik, M.E.; Islam, M.M.; Hossain, Q.S. A review on neural network techniques for the prediction of road traffic accident severity. *Asian Transp. Stud.* **2021**, *7*, 100040. [CrossRef]
50. Fawcett, T. An introduction to ROC analysis. *Pattern Recognit. Lett.* **2006**, *27*, 861–874. [CrossRef]
51. Sokolova, M.; Lapalme, G. A systematic analysis of performance measures for classification tasks. *Inf. Process. Manag.* **2009**, *45*, 427–437. [CrossRef]
52. Ullah, I.; Liu, K.; Yamamoto, T.; Zahid, M.; Jamal, A. Modeling of machine learning with SHAP approach for electric vehicle charging station choice behavior prediction. *Travel Behav. Soc.* **2023**, *31*, 78–92. [CrossRef]
53. Diallo, A.O.; Lozenguez, G.; Doniec, A.; Mandiau, R. Estimation of minority modes of transportation based on machine learning approach. *Procedia Comput. Sci.* **2022**, *201*, 265–272. [CrossRef]
54. Moussaoui, A.E.E.; Moussaoui, T.E.; Benbba, B.; Jaegler, A.; Andaloussi, Z.E. Understanding the Choice of Collection & Delivery Point by the E- Consumer via a Machine Learning Model: Moroccan Case Study. *Procedia Comput. Sci.* **2022**, *210*, 204–211. [CrossRef]
55. Batool, S.Q.; Sajid, M.A.; Shaheen, I. Gender and higher education in Pakistan. *Int. J. Gend. Women's Stud.* **2013**, *1*, 15–28.
56. Rehman, Z.; Baloch, S.; Zia, A. Women Disconnected: Feminist Case Studies on the Gender Digital Divide Amidst COVID-19. Islamabad. 2021. Available online: https://www.digitalrightsmonitor.pk/wp-content/uploads/2021/01/Women-Disconnected-Gender-Digital-Divide-in-Pakistan.pdf (accessed on 13 April 2024).
57. Paksitan Bureau of Statistics. Salient Features of Final Results Census-2017 [Online]. Available online: https://www.pbs.gov.pk/sites/default/files/population/2017/sailent_feature_census_2017.pdf (accessed on 23 April 2025).
58. Nicolau, J.L.; Más, F.J. The influence of distance and prices on the choice of tourist destinations: The moderating role of motivations. *Tour. Manag.* **2006**, *27*, 982–996. [CrossRef]
59. Center for Economic Research in Pakistan. Women's Mobility Program. 2023. Available online: https://www.cerp.org.pk/gender/ (accessed on 23 April 2025).
60. Loukaitou-Sideris, A. Fear and safety in transit environments from the women's perspective. *Secur. J.* **2014**, *27*, 242–256. [CrossRef]

61. Susilo, Y.O.; Abenoza, R.; Woodcock, A.; Liotopoulos, F.; Duarte, A.; Osmond, J.; Georgiadis, A.; Hrin, G.R.; Bellver, P.; Fornari, F.; et al. Findings from measuring door-to-door travellers' travel satisfaction with traditional and smartphone app survey methods in eight European cities. *Eur. J. Transp. Infrastruct. Res.* **2017**, *17*, 384–410. [CrossRef]
62. Gao, J.; Kerstetter, D.L. Using an intersectionality perspective to uncover older Chinese female's perceived travel constraints and negotiation strategies. *Tour. Manag.* **2016**, *57*, 128–138. [CrossRef]
63. Durko, A.M.; Stone, M.J. Even lovers need a holiday: Women's reflections of travel without their partners. *Tour. Manag. Perspect.* **2017**, *21*, 18–23. [CrossRef]
64. Wilson, E.; Little, D.E. The Solo Female Travel Experience: Exploring the 'Geography of Women's Fear'. *Curr. Issues Tour.* **2008**, *11*, 167–186. [CrossRef]
65. Tan, W.-K. Repeat visitation: A study from the perspective of leisure constraint, tourist experience, destination images, and experiential familiarity. *J. Destin. Mark. Manag.* **2017**, *6*, 233–242. [CrossRef]
66. Karl, M.; Bauer, A.; Ritchie, W.B.; Passauer, M. The impact of travel constraints on travel decision-making: A comparative approach of travel frequencies and intended travel participation. *J. Destin. Mark. Manag.* **2020**, *18*, 100471. [CrossRef]
67. Alegre, J.; Mateo, S.; Pou, L. An analysis of households' appraisal of their budget constraints for potential participation in tourism. *Tour. Manag.* **2010**, *31*, 45–56. [CrossRef]
68. Alegre, J.; Mateo, S.; Pou, L. Tourism participation and expenditure by Spanish households: The effects of the economic crisis and unemployment. *Tour. Manag.* **2013**, *39*, 37–49. [CrossRef]
69. Nicolau, J.L.; Más, F.J. Heckit modelling of tourist expenditure: Evidence from Spain. *Int. J. Serv. Ind. Manag.* **2005**, *16*, 271–293. [CrossRef]
70. Domènech, A.; Gutiérrez, A. Determinants of cruise tourists' expenditure visiting port cities. *Tour. Rev.* **2020**, *75*, 793–808. [CrossRef]
71. Chen, C.-C.; Petrick, J.F. The Roles of Perceived Travel Benefits, Importance, and Constraints in Predicting Travel Behavior. *J. Travel Res.* **2016**, *55*, 509–522. [CrossRef]
72. Chen, C.-C.; Zou, S.; Petrick, J.F. Is Travel and Tourism a Priority for You? A Comparative Study of American and Taiwanese Residents. *J. Travel Res.* **2019**, *58*, 650–665. [CrossRef]
73. Khan, M.J.; Chelliah, S.; Ahmed, S. Intention to visit India among potential travellers: Role of travel motivation, perceived travel risks, and travel constraints. *Tour. Hosp. Res.* **2019**, *19*, 351–367. [CrossRef]
74. Xie, L.; Ritchie, B.W. The motivation, constraint, behavior relationship: A holistic approach for understanding international student leisure travelers. *J. Vacat. Mark.* **2019**, *25*, 111–129. [CrossRef]
75. Humagain, P.; Singleton, P.A. Investigating travel time satisfaction and actual versus ideal commute times: A path analysis approach. *J. Transp. Health* **2020**, *16*, 100829. [CrossRef]
76. Ye, R.; De Vos, J.; Ma, L. Analysing the association of dissonance between actual and ideal commute time and commute satisfaction. *Transp. Res. Part A Policy Pract.* **2020**, *132*, 47–60. [CrossRef]
77. Ory, D.T.; Mokhtarian, P.L. Modeling the structural relationships among short-distance travel amounts, perceptions, affections, and desires. *Transp. Res. Part A Policy Pract.* **2009**, *43*, 26–43. [CrossRef]
78. Luiu, C.; Tight, M.; Burrow, M. The unmet travel needs of the older population: A review of the literature. *Transp. Rev.* **2017**, *37*, 488–506. [CrossRef]
79. Alvarez, M.D.; Korzay, M. Turkey as a Heritage Tourism Destination: The Role of Knowledge. *J. Hosp. Mark. Manag.* **2011**, *20*, 425–440. [CrossRef]
80. Angelovska, J.; Bilic, S.; Angelovska, N. The impact of environmental concern and awareness on consumer behavior. *J. Int. Environ. Appl. Sci.* **2012**, *7*, 406–416.
81. Pan, S.-L.; Chou, J.; Morrison, A.M.; Huang, W.-S.; Lin, M.-C. Will the Future Be Greener? The Environmental Behavioral Intentions of University Tourism Students. *Sustainability* **2018**, *10*, 634. [CrossRef]
82. Sharifpour, M.; Walters, G.; Ritchie, B.W. Risk perception, prior knowledge, and willingness to travel: Investigating the Australian tourist market's risk perceptions towards the Middle East. *J. Vacat. Mark.* **2014**, *20*, 111–123. [CrossRef]
83. Sharifpour, M.; Walters, G.; Ritchie, B.W.; Winter, C. Investigating the Role of Prior Knowledge in Tourist Decision Making: A Structural Equation Model of Risk Perceptions and Information Search. *J. Travel Res.* **2013**, *53*, 307–322. [CrossRef]
84. Yang, E.C.L.; Sharif, S.P.; Khoo-Lattimore, C. Tourists' risk perception of risky destinations: The case of Sabah's eastern coast. *Tour. Hosp. Res.* **2015**, *15*, 206–221. [CrossRef]
85. Chen, C.-F.; Tsai, D. How destination image and evaluative factors affect behavioral intentions? *Tour. Manag.* **2007**, *28*, 1115–1122. [CrossRef]
86. Powers, D.M.W. Evaluation: From precision, recall and F-measure to ROC, informedness, markedness & correlation. *J. Mach. Learn. Technol.* **2011**, *2*, 2229–3981.
87. Verplanken, B.; Aarts, H.; Van Knippenberg, A. Habit, information acquisition, and the process of making travel mode choices. *Eur. J. Soc. Psychol.* **1997**, *27*, 539–560. [CrossRef]

88. Bamberg, S.; Ajzen, I.; Schmidt, P. Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action. *Basic Appl. Soc. Psychol.* **2003**, *25*, 175–187. [CrossRef]
89. De Vos, J.; Witlox, F. Travel satisfaction revisited. On the pivotal role of travel satisfaction in conceptualising a travel behaviour process. *Transp. Res. Part A Policy Pract.* **2017**, *106*, 364–373. [CrossRef]
90. Um, S.; Crompton, J.L. Attitude determinants in tourism destination choice. *Ann. Tour. Res.* **1990**, *17*, 432–448. [CrossRef]
91. Dolnicar, S. Market segmentation analysis in tourism: A perspective paper. *Tour. Rev.* **2019**, *75*, 45–48. [CrossRef]
92. Kazemeini, A.; Kermanshah, A. Promoting Sustainable Transport in Developing Countries: A Case Study of University Students in Tehran. *Future Transp.* **2023**, *3*, 858–877. [CrossRef]
93. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]
94. McFadden, D. The Choice Theory Approach to Market Research. *Mark. Sci.* **1986**, *5*, 275–297. [CrossRef]
95. Mckercher, B.; Lew, A.A. Distance Decay and the Impact of Effective Tourism Exclusion Zones on International Travel Flows. *J. Travel Res.* **2003**, *42*, 159–165. [CrossRef]
96. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
97. Swait, J. Choice set generation within the generalized extreme value family of discrete choice models. *Transp. Res. Part B Methodol.* **2001**, *35*, 643–666. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.