

Understanding Travelers’ Attitudes Toward Sustainability in City Trip Recommendations

Ashmi Banerjee^{1*} and Wolfgang Wörndl¹

¹Technical University of Munich, Germany.

*Corresponding author(s). E-mail(s): ashmi.banerjee@tum.de;
Contributing authors: woerndl@in.tum.de;

Abstract

Tourism is a significant driver of economic development, but also a major contributor to environmental challenges. As awareness of sustainability grows, travelers face complex trade-offs between personal preferences (e.g., cost, interest alignment) and environmental responsibility. This paper investigates these trade-offs through a user-centric study with 39 participants, combining Likert-scale questions to capture stated preferences and a Discrete Choice Experiment (DCE) to model revealed preferences. The attributes analyzed were destination popularity, crowding, budget, environmental impact, and interest match. Our results show that although participants voiced strong support for sustainability in principle, the DCE indicated that budget constraints, crowd avoidance, and interest alignment were stronger drivers of choice. Notably, "moderately popular" destinations were most preferred, suggesting a desire for a balance between discovery and reliability. These findings provide crucial insights for designing recommender systems that can effectively nudge users toward more sustainable travel by aligning environmental benefits with personal priorities like cost savings and better experiences.

Keywords: Tourism Recommender Systems, Sustainable Tourism, User-Centric Design, User Studies

1 Introduction

Motivation. Tourism drives economic growth but also contributes substantially to carbon emissions, overtourism, and ecological degradation [1]. Despite rising awareness, many travelers struggle to reconcile personal preferences (e.g., cost, convenience,

interest alignment) with sustainability goals, leading to the well-documented "attitude-behavior gap," where pro-environmental intentions often fail to translate into practice [2, 3].

Tourism Recommender Systems (TRS) can help bridge this gap by embedding sustainability considerations into decision support. Prior work has explored integrating environmental metrics into TRS [4, 5], applying multi-objective optimization for sustainable planning [6], and using proactive AI to generate eco-friendly itineraries [7]. Yet, a challenge remains: understanding how travelers balance sustainability against dominant drivers such as cost and interest match. Stated-preference surveys capture intentions but often fail to predict actual behavior in complex decision contexts.

To address this limitation, hybrid approaches combining stated and revealed preference methods are gaining traction. In particular, Discrete Choice Experiments (DCEs) present travelers with realistic, multi-attribute scenarios that reveal the implicit trade-offs underlying their choices [8, 9]. This approach enables a more precise quantification of how sustainability competes with other decision drivers [9].

Related Work. Research on sustainability in TRS can be clustered into several main directions: (1) integrating sustainability indicators (such as CO2e emissions, destination popularity measured using user generated content, seasonality) to guide tourists toward eco-friendly and less crowded destinations [4, 5]; (2) designing user interfaces and digital nudges to influence pro-environmental travel choices [10, 11]; (3) adopting multistakeholder fairness frameworks to balance the interests of tourists, local communities, and the environment [12, 13]; and (4) applying behavioral models (e.g., regret minimization, utility maximization) and user studies to evaluate and improve the effectiveness of sustainable tourism recommendations [14].

Contributions. Building on prior applications of choice models in tourism [6], our study employs a mixed-method design that integrates Likert-scale surveys with a DCE. This allows us to (1) measure stated attitudes toward sustainability, cost, crowdedness, and destination popularity, and (2) compare them with revealed choices in controlled trade-off scenarios. Through this design, we isolate the relative weight of sustainability when directly contrasted with budgetary or experiential factors.¹

The contributions of this work are threefold:

- Empirical insights into the hierarchy of traveler preferences, highlighting when sustainability is outweighed by other factors.
- Actionable design principles for recommender systems that use behavioral insights to nudge users toward responsible choices without sacrificing personalization.
- A reusable survey application that combines stated- and revealed-preference methods, offering a flexible tool for future research.

The paper is structured as follows: Section 2 details our hybrid methodology; Section 3 presents findings on the trade-offs underlying sustainable travel decisions; Section 4 discusses implications for system design; and Section 5 concludes with future directions.

¹We use *sustainability* and *environmental impact* (e.g., emissions) interchangeably to denote the ecological implications of travel choices. Likewise, *crowdedness* and *seasonality* are used synonymously, as both capture temporal variations in demand affecting congestion and experience.

2 User Study Design

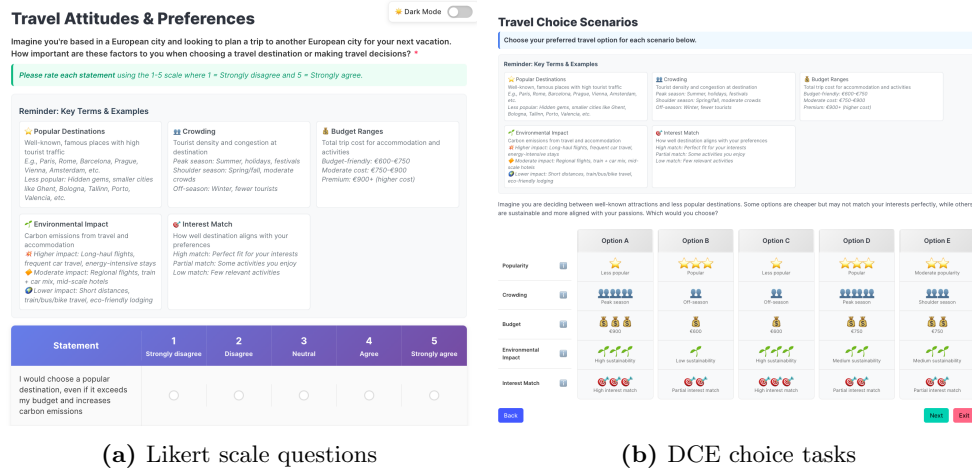


Figure 1: Screenshots of the survey application interface showing Likert scale questions and DCE choice tasks

To examine the sustainability and interest alignment trade-off in tourism, we conducted a user study using a hybrid methodology. The study systematically compared travelers’ stated environmental attitudes with their revealed preferences in realistic choice scenarios, enabling us to identify and quantify trade-offs.

2.1 Objectives

The study pursued four objectives:

- **Assess stated attitudes:** Collect self-reported preferences on sustainability, budget, crowdedness, and travel factors via Likert-scale questions (Figure 1a).
- **Model behavioral preferences:** Apply a Discrete Choice Experiment (DCE) to capture revealed trade-offs across competing trip attributes (Figure 1b).
- **Quantify the interest-alignment trade-off:** Compare stated attitudes with DCE outcomes to reveal factors overriding sustainable intentions.
- **Inform recommender nudges:** Translate trade-offs into design principles that align sustainability with behavioral drivers such as cost and convenience.

2.2 Methodology

Survey Instrument. A custom web application was developed using ReactJS² and hosted on Firebase³ to implement the survey, allowing dynamic interaction and adaptive elements. After participants reviewed the study details and provided informed consent, the questionnaire proceeded in three stages:

1. **Traveler Profile:** General travel behaviors and preferences (e.g., activities, budget, frequency) were recorded.
2. **Attitudes:** Travel trade-offs were measured using 5-point Likert-scale items, supported by a persistent glossary for consistent interpretation (Figure 1a).
3. **DCE Tasks:** Participants completed eight choice tasks, each presenting five trip alternatives defined by *Popularity*, *Crowding*, *Budget*, *Environmental Impact*, and *Interest Match*. Since a full factorial design would be impractical, the combinations of attributes were manually curated to highlight meaningful trade-offs such as budget vs. interest alignment or popularity vs. sustainability, etc. Two additional tasks served as attention checks and were excluded from estimation. The final dataset included $N = 39$ (participants) \times 8 (choice tasks) \times 5 (options) = 1560 alternative-level observations.

The interface included randomized ordering, explanatory tooltips, and validation features to reduce cognitive load and enhance data quality. Screenshots of the Likert scale and DCE interfaces are shown in Figure 1.

Participants. We recruited participants via Prolific (eligibility: age ≥ 18 , Europe-based, leisure travel history). The survey took 10-15 minutes to complete, and after applying attention checks, 39 participants were retained for analysis.

3 Results

In this section, we present the key findings from our user study, focusing on both stated preferences from Likert scale ratings and revealed preferences from the Discrete Choice Experiment (DCE). We analyze how travelers prioritize different attributes when making travel decisions and identify the trade-offs that define the attitude-behavior gap in sustainable tourism.

3.1 Stated Preferences from Likert Scale Ratings

The Likert scale responses (Figure 2) capture participants’ stated attitudes toward key travel trade-offs, including sustainability, budget, interest alignment, popularity, and seasonality. Table 1 lists the specific statements and their codes, which are visualized in Figure 2, providing a benchmark for comparison with the DCE results.

Sustainability Preferences (S1-S3) Sustainability proved to be a weak standalone motivator for travel decisions. Respondents showed little proactive interest in minimizing their environmental impact (Figure 2a), with only 8% agreeing they try to minimize carbon emissions (S1) and a plurality of 49% disagreeing. This reluctance

²<https://react.dev>

³<https://firebase.google.com>

Code	Statement
S1	I try to minimize carbon emissions when choosing a destination
S2	I choose to travel in the off-season to reduce my carbon footprint
S3	I would travel during the off-season to reduce carbon emissions, even if the destination matches my interests less well
B1	I would stick to my budget even if it results in higher emissions
B2	I would choose a trip within my budget even if it does not perfectly match my interests
B3	I would travel during the off-season to stay within budget and reduce my carbon footprint, even if I miss some peak-season activities
IM1	I prioritize destinations that align with my interests, even if they have a higher carbon footprint
IM2	I would choose a less popular destination that matches my interests, even if it exceeds my budget
IM3	I would choose a destination that matches my interests, even if it exceeds my budget and is during peak season
P1	I would visit a popular destination during peak season, even if it does not align perfectly with my interests
P2	I would choose a popular destination, even if it exceeds my budget and increases carbon emissions
P3	I prefer visiting a popular destination during peak season, even if it is very crowded
CR1	I prefer traveling to a less well-known destination during the off-season to avoid crowds
CR2	I choose to travel in the off-season to reduce my carbon footprint
CR3	I would travel during the off-season to stay within budget and reduce my carbon footprint, even if I miss some peak-season activities

Table 1: User Importance Ratings for Travel Attributes (Likert Scale)

to prioritize environmental impact was even more pronounced when a direct trade-off was introduced; for statement S3, a majority of 57% (13% Strongly Disagree, 44% Disagree) were unwilling to compromise on their interests to reduce emissions. Similarly, using sustainability as the sole reason for off-season travel (S2) was met with disapproval from 46% of respondents (18% Strongly Disagree, 28% Disagree), compared to only 13% who agreed.

Budget Constraints(B1-B3) Financial constraints proved to be a significantly more powerful driver of behavior than sustainability (Figure 2b). A decisive 67% of respondents (41% Agree, 26% Strongly Agree) confirmed they would prioritize their budget even if it led to higher emissions (B1). While the trade-off between budget and personal interests was more contentious (B2), with 44% agreeing to compromise interests for budget versus 31% disagreeing, budget became a potent tool for encouraging other behaviors. When framed as a way to both save money and reduce one’s carbon footprint (B3), traveling off-season was met with overwhelming approval from 69% of users (38% Agree, 31% Strongly Agree).

Interest Match (IM1-IM3) Aligning travel with personal interests is unequivocally the most dominant factor for users (Figure 2c). An overwhelming 84% of respondents (58% Agree, 26% Strongly Agree) prioritize their interests even at the expense of a higher carbon footprint (IM1). The primacy of interest is so strong that 45%

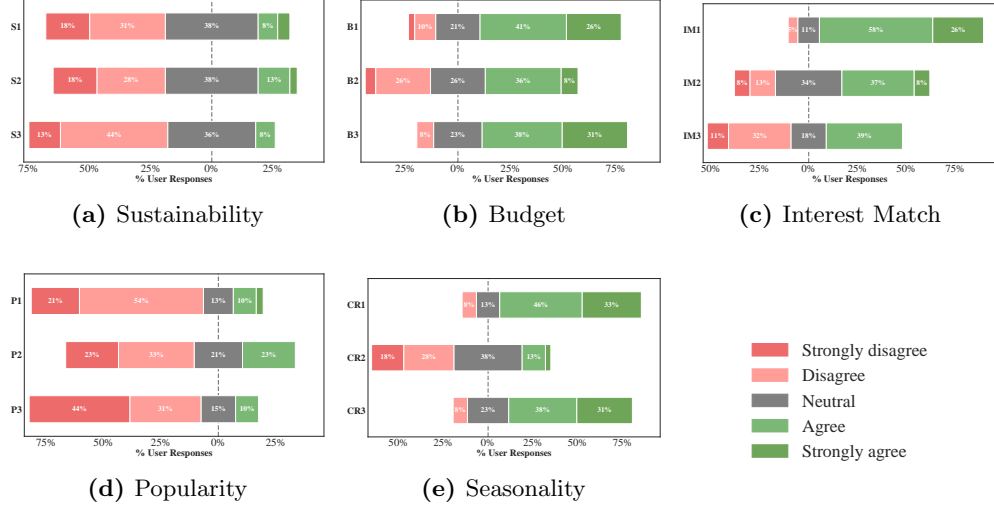


Figure 2: Visualizations of user importance ratings for travel attributes (see statement codes in Table 1)

(37% Agree, 8% Strongly Agree) would consider exceeding their budget for a better-matched, less popular destination (IM2). However, this priority is not absolute; when faced with the combined negative factors of exceeding a budget and traveling during peak season (IM3), support dropped significantly, with 43% of users disagreeing (11% Strongly Disagree, 32% Disagree) and only 39% agreeing.

Popularity (P1-P3) The appeal of a "popular" destination is a weak motivator, consistently outweighed by other preferences (Figure 2d). A striking 75% of users (44% Strongly Disagree, 31% Disagree) rejected the idea of visiting a popular destination during peak season if it was very crowded (P3). This aversion to compromising core preferences was echoed in the response to P1, where another 75% (21% Strongly Disagree, 54% Disagree) stated they would not visit a popular location if it didn't align with their interests. The notion of choosing a popular destination despite it exceeding one's budget and increasing emissions (P2) was also rejected by a majority of 56% (23% Strongly Disagree, 33% Disagree).

Seasonality / Crowding (CR1-CR3) The data reveal a definitive and strong preference for avoiding crowds (Figure 2e). An overwhelming 79% of respondents (46% Agree, 33% Strongly Agree) affirmed they prefer traveling to less well-known destinations during the off-season to avoid crowds (CR1), making it one of the clearest points of consensus. While the goal of crowd avoidance is popular, the framing of the solution is critical. Simply suggesting off-season travel to reduce one's carbon footprint (CR2) was met with disagreement from 46% of users. In stark contrast, when off-season travel was presented as a way to both stay within budget and be sustainable (CR3), it garnered strong support from 69% (38% Agree, 31% Strongly Agree), demonstrating that travelers are most receptive to strategies that combine practical benefits with desirable outcomes like crowd avoidance.

In summary, the stated preferences through the Likert responses highlight a hierarchy of preferences: (1) interest alignment and crowd avoidance dominate, (2) budget is consistently important, and (3) sustainability is valued but less decisive when in conflict with personal interests.

3.2 Revealed Preferences from Discrete Choice Experiment (DCE)

The DCE provides insight into revealed preferences — how respondents behave when making concrete trade-offs between attributes. Participants completed a series of forced-choice trials in which they chose their preferred destination from five alternatives that varied on popularity, crowdedness (seasonality), budget, sustainability, and interest match. An example DCE choice screen is shown in Figure 1b, which made attribute differences explicit during selection.

We used a multinomial logistic regression (MNLogit) [15] to analyze destination choices, where the dependent variable is categorical and reflects the selected destination. The model was estimated using maximum likelihood estimation (MLE) [16] on a sample of $N = 1560$ choice observations (as explained in Section 2). This model allows us to infer the importance of each attribute level based on the choices participants actually made.

Predictor variables included destination attributes: popularity, crowdedness, budget, sustainability, and interest match. Each categorical attribute was coded as a set of binary (dummy) variables. Model estimation was performed on the full sample, enabling comparison of attribute effects across segments. Statistical significance was assessed using standard errors, z -statistics, and p -values; 95% confidence intervals were reported for all coefficients.

3.2.1 Sample Composition, Dummy Counts and Model Fit Statistics

In the discrete choice experiment, categorical attributes such as popularity, crowding, budget, sustainability, and interest match were one-hot encoded into binary indicators (dummy-counts) to ensure sufficient variation across levels for model estimation and scenarios with partial interest match were intentionally oversampled.

The multinomial logit model estimated for the discrete choice experiment showed a pseudo R^2 of 0.1485, a log-likelihood of -664.73 , and a null log-likelihood of -780.63 . The pseudo R^2 indicates the improvement in fit over a model with no predictors, while the log-likelihood quantifies how well the model predicts observed choices. The model converged successfully, and the likelihood ratio test was highly significant ($p < 0.001$), confirming that the included attributes meaningfully influenced participants' choices. In this framework, each estimated coefficient reflects the direction and magnitude of an attribute's effect on utility (positive values increasing choice probability, negative values decreasing it). The corresponding odds ratios express these effects in multiplicative terms, indicating how the likelihood of choosing an alternative changes for a

one-unit increase in the predictor (i.e., presence of a dummy-coded attribute level). Together, these measures provide a robust basis for interpreting the relative importance of attributes and the trade-offs participants made across experimental conditions [15, 17].

3.2.2 Interpretation of Travel Choice Predictors

The DCE model reveals how attributes influenced the probability of destination choice. The significant predictors are summarized and interpreted in Table 2. The multinomial logistic regression results highlight several clear patterns in traveler decision-making.

Attribute Level	Coefficient (β)	Std. Error	P-value	Odds Ratio
<i>Reference: Not Popular, Off-Season, Low Budget, High Sustainability, Perfect Match</i>				
Intercept	-0.104	0.154	0.497	0.90
Popularity				
Moderate (vs. Not Popular)	1.41	0.53	0.007	4.10
Popular (vs. Not Popular)	0.35	0.18	0.047	1.42
Crowdedness				
Peak Season (vs. Off-Season)	-0.71	0.20	0.001	0.49
Shoulder Season (vs. Off-Season)	-0.26	0.55	0.636	0.77
Budget				
750 EUR (vs. Low)	0.71	0.81	0.380	2.04
900 EUR (vs. Low)	-1.65	0.21	<0.001	0.19
Sustainability				
Low (vs. High)	-0.73	0.22	0.001	0.48
Medium (vs. High)	-1.18	0.77	0.126	0.31
Interest Match				
Partial (vs. Perfect)	-1.44	0.21	<0.001	0.24

Table 2: Multinomial logistic regression results for travel choice predictors. Significant coefficients ($p < 0.05$) are shown in bold. Reference levels: Not Popular, Off-Season, Low Budget, High Sustainability, Perfect Match.

Interest Match is Paramount. The strongest predictor of choice was alignment with traveler interests. Trips with only a “Partial” interest match were approximately 76% less likely to be chosen than those with a “Perfect” match (Odds Ratio = 0.24, $p < 0.001$), emphasizing that personal relevance is a dominant, non-negotiable factor in travel decisions.

Budget is a Hard Constraint. The high-budget option (EUR 900) significantly reduced the likelihood of selection, making a destination about 81% less likely to be chosen relative to the low-budget baseline (Odds Ratio = 0.19, $p < 0.001$). This indicates that travelers are highly sensitive to price and actively avoid expensive options, while the mid-range budget (EUR 750) was not a significant predictor.

The “Sweet Spot” of Popularity. Travelers preferred destinations that were neither unknown nor overly popular. A “Moderately Popular” destination was over

four times more likely to be chosen than a “Not Popular” one (Odds Ratio = 4.10, $p = 0.007$), while “Popular” destinations were also preferred but to a lesser extent (Odds Ratio = 1.42, $p = 0.047$). This pattern suggests that travelers seek destinations that are vetted and reliable but not yet subject to overtourism.

Crowds and Sustainability Influence Choice.

- *Crowdedness*: Trips during “Peak Season” were about 51% less likely to be chosen than off-season alternatives (Odds Ratio = 0.49, $p = 0.001$), demonstrating a strong aversion to crowded periods. “Shoulder Season” was not significant, indicating it acts as a neutral baseline.
- *Sustainability*: Destinations with “Low Sustainability” were about 52% less likely to be selected than those with “High Sustainability” (Odds Ratio = 0.48, $p = 0.001$). Medium sustainability was not significant, suggesting that while travelers penalize the worst environmental offenders, they may not strongly differentiate between good and excellent options.

Summary of Effects. Overall, positive predictors included moderate and high popularity, while negative predictors were peak season crowdedness, high budget, low sustainability, and partial interest match. Non-significant predictors such as shoulder season, mid-range budget, and medium sustainability acted as neutral baselines. Collectively, these results demonstrate that travelers prioritize a balanced combination of popularity, cost, sustainability, and personal interest alignment when selecting destinations, actively avoiding extremes that conflict with their preferences. The odds ratios provide a clear quantitative measure of how each attribute level affects the probability of being chosen.

3.3 Comparing Stated and Revealed Preferences

Comparing the two methodologies — Likert-scale (Section 3.1) and discrete choice experiment (DCE) (Section 3.2), highlights a key distinction between what travelers report valuing and how they make decisions when confronted with realistic trade-offs.

Convergence. Both approaches show strong agreement on several decision-making factors. Budget constraints and avoidance of peak-season crowds emerge consistently as primary considerations. High interest alignment is also universally prioritized, indicating that travelers seek experiences that closely match their preferences. This convergence suggests that strategies emphasizing interest-based personalization and off-peak travel incentives are likely to resonate with a broad audience.

Divergence and the Attitude-Behavior Gap. A notable divergence appears regarding sustainability. In stated preference measures, respondents express a strong abstract desire to choose sustainable options (Figure 2a, S1). However, the DCE reveals that, although “low sustainability” is a negative driver of choice, its effect must be weighed against other attributes. Specifically, the DCE shows that travelers frequently face trade-offs between sustainability and interest alignment: both “low sustainability” and “partial interest match” are negative predictors, yet the strong preference for personal interest often overrides sustainability concerns (S3, IM1). This discrepancy highlights a practical trade-off: interventions aimed at promoting sustainable tourism

must consider the strength of travelers’ interest alignment preferences. For instance, offering sustainable options that are also highly engaging or tailored to traveler interests may increase uptake.

Refining Popularity Preferences. Likert-scale data (Figure 2d) initially suggested a simple aversion to popular destinations. The DCE provides a more nuanced understanding: a strong positive coefficient for “moderate popularity” indicates that travelers do not favor completely unknown destinations. Instead, they seek locations that are vetted and reliable but not yet impacted by overtourism, reflecting a preference for a balanced “sweet spot” of popularity.

Overall, integrating both stated and revealed preference measures allows for more informed decision-support strategies: while Likert scale responses provide insight into aspirational values, DCE-based revealed preferences uncover the realistic trade-offs that guide actual travel behavior. Although the DCE followed the Likert section and may have introduced minor priming effects, the divergence between stated and revealed preferences suggests this influence was negligible.

4 Aligning Traveler Preferences with Sustainable Travel Choices

Our findings confirm the existence of a prominent attitude-behavior gap in sustainable tourism. While travelers express an intention to be environmentally conscious, this aspiration is frequently overridden by more immediate, tangible factors such as cost, convenience, and personal fulfillment. Consequently, a recommender system that simply instructs users to “be more sustainable” is unlikely to be effective. Instead, promoting sustainable travel requires aligning sustainability with other, more dominant user values. Our study suggests several actionable strategies:

- **Leveraging aversion to crowds:** Travelers show a strong dislike for crowded, peak-season destinations. This preference aligns naturally with the sustainability goal of reducing seasonal tourism pressure. Recommender systems can frame off-season or shoulder-season travel not only as environmentally beneficial, but also as a way to enjoy a “more authentic, less crowded experience.”
- **Connecting sustainability to budget:** Since budget is a primary constraint, systems can highlight how sustainable choices—such as traveling off-season, selecting less popular (and often more affordable) destinations, or using public transport—can simultaneously reduce costs.
- **Promoting the “sweet spot”:** The observed preference for “moderately popular” destinations is a key insight. Systems can curate and recommend these locations as attractive alternatives to over-touristed hotspots, balancing user desire for familiarity and reliability with the need to distribute tourism more sustainably.

As summarized in Table 3, each key user preference can be leveraged to design sustainable travel nudges that align with travelers’ priorities. Ultimately, effective nudges in this context are not about guilt or obligation, but about intelligently framing sustainable options as superior, user-centric choices that satisfy multiple traveler priorities.

User Preference / Constraint	Observed Behavior / Importance	Sustainable Travel Nudges	Rationale
Interest Match	Paramount (highest odds ratio)	Suggest destinations aligning with user interests that are also sustainable	Ensures nudges are adopted by prioritizing personal relevance
Budget	High budget deters choices	Highlight cost-saving sustainable options (off-season, less popular destinations, public transport)	Aligns sustainability with financial benefits
Crowdedness	Avoids peak season	Recommend shoulder/off-season travel	Reduces congestion and environmental impact
Popularity	Prefers moderate popularity	Feature moderately popular destinations over hotspots	Balances novelty and sustainability
Sustainability	Negative impact only when extreme	Emphasize environmental benefits in combination with other priorities	Integrates sustainability with dominant user values

Table 3: Mapping user preferences and constraints to actionable sustainable travel nudges. This table illustrates how recommender systems can leverage observed travel behaviors to promote environmentally conscious choices without compromising key user priorities.

5 Conclusion

This study shows that tourism choices involve trade-offs among interest alignment, budget, crowding, popularity, and sustainability. While travelers often express pro-environmental intentions, actual choices are more influenced by cost and personal interest. Our discrete choice experiment suggests that integrating sustainability into user values—through off-season travel, moderately popular destinations, or cost-saving strategies—can promote more responsible tourism. These findings underscore the potential of user-centric recommender systems to guide sustainable travel decisions.

This study has some limitations. First, the final analytic sample was small ($n = 39$ after attention checks). Second, the discrete choice experiment relied on hypothetical trip scenarios; although these were designed to approximate realistic trade-offs, they cannot fully capture the financial or emotional stakes of actual travel decisions. Finally, we did not analyze demographic effects, as the sample size and composition did not support robust subgroup analyses. Future work can build on this study by scaling to larger and more diverse populations, integrating behavioral data beyond self-report, and testing sustainability nudges in real-world recommender systems.

GenAI Usage Disclosure

We used ChatGPT (OpenAI), Claude (Anthropic), and Gemini (Google) for code suggestions, and Grammarly for grammar and clarity checks. All outputs were critically reviewed and revised to ensure accuracy and originality, and we take full responsibility for the content of this draft.

References

- [1] Gössling, S.: Tourism, information technologies and sustainability: an exploratory review. *Journal of Sustainable Tourism* **25**(7), 1024–1041 (2017)

- [2] Müller, A., Bács, Z., Fenyves, V., Kovács, S., Lengyel, A., Bácsné, E.: Demographic influences on environmental attitudes and actions: An analysis of the attitude-behavior gap. *Geojournal of Tourism and Geosites* **60**, 1028–1040 (2025)
- [3] Juvan, E., Dolnicar, S.: The attitude–behaviour gap in sustainable tourism. *Annals of tourism research* **48**, 76–95 (2014)
- [4] Banerjee, A., Mahmudov, T., Adler, E., Aisyah, F.N., Wörndl, W.: Modeling sustainable city trips: Integrating co₂e emissions, popularity, and seasonality into tourism recommender systems. TUM School of Computation, Information and Technology, Technical University of Munich (2024)
- [5] Banerjee, A., Satish, A., Wörndl, W.: Enhancing tourism recommender systems for sustainable city trips using retrieval-augmented generation. In: *International Workshop on Recommender Systems for Sustainability and Social Good*, pp. 19–34 (2024). Springer
- [6] Arbolino, R., Boffardi, R., De Simone, L., Ioppolo, G.: Multi-objective optimization technique: A novel approach in tourism sustainability planning. *Journal of Environmental Management* **285**, 112016 (2021)
- [7] Li, C., Zheng, W.: Nipping trouble in the bud: A proactive tourism recommender system. *Information & Management* **62**(1), 104062 (2025)
- [8] Almomani, A., Saavedra, P., Barreiro, P., Durán, R., Crujeiras, R., Loureiro, M., Sánchez, E.: Application of choice models in tourism recommender systems. *Expert Systems* **40**(3), 13177 (2023)
- [9] Li, Y., Yao, E., Yang, Y., Li, B.: Understanding tourism travel behavior by combining revealed preference survey and mobile phone data. *Transportation Research Part A: Policy and Practice* **194**, 104408 (2025)
- [10] Banerjee, A., Mahmudov, T., Wörndl, W.: Green destination recommender: A web application to encourage responsible city trips. In: *Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation, and Personalization* (2024)
- [11] Mauro, N., Scarpinati, L., Ferrero, F., Geninatti Cossatin, A., Mattutino, C.: Point-of-interest recommender systems: Nudging towards sustainable tourism. In: *Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization*, pp. 491–495 (2024)
- [12] Banik, P., Banerjee, A., Wörndl, W.: Understanding user perspectives on sustainability and fairness in tourism recommender systems. In: *Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization*, pp. 241–248 (2023)

- [13] Felfernig, A., Wundara, M., Tran, T.N.T., Polat-Erdeniz, S., Lubos, S., El Mansi, M., Garber, D., Le, V.-M.: Recommender systems for sustainability: overview and research issues. *Frontiers in big Data* **6**, 1284511 (2023)
- [14] Gao, Q., Cui, S., Shi, P., Li, Z.: Exploring tourists' preferences and willingness to pay for national park recreation improvements based on regret and utility comparison. *Scientific Reports* **14**(1), 21524 (2024)
- [15] Kwak, C., Clayton-Matthews, A.: Multinomial logistic regression. *Nursing research* **51**(6), 404–410 (2002)
- [16] Pan, J.-X., Fang, K.-T.: Maximum likelihood estimation. In: *Growth Curve Models and Statistical Diagnostics*, pp. 77–158. Springer, New York, NY (2002). https://doi.org/10.1007/978-0-387-21812-0_3
- [17] Hu, B., Shao, J., Palta, M.: Pseudo-r² in logistic regression model. *Statistica Sinica*, 847–860 (2006)