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Data-Driven Techno-Behavioral Segmentation of Post-Pandemic Tourists Using TwoStep Cluster Analysis

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Abstract. Post-pandemic tourism is characterized by increasing behavioral heterogeneity as digital technologies reshape travel planning and mobility practices, challenging traditional demographic-based segmentation. This study develops a techno-behavioral, data-driven segmentation framework within the Smart Tourism Ecosystem perspective by conceptualizing digital adoption as a mediating mechanism between socio-demographic attributes and travel behavior. Using survey data from 805 domestic tourists in Yogyakarta, Indonesia, TwoStep Cluster Analysis (log-likelihood distance; BIC-based cluster selection) identifies two distinct segments: Digital Leisure Travelers (DLT) and Budget-Conscious Digital Natives (BDN). The clustering solution demonstrates fair quality (Silhouette = 0.32). Predictor-importance and validation tests indicate that income, education, generational cohort, and digital application use are the strongest discriminators, while itinerary intensity differs significantly between clusters ($p < 0.001$; $\eta^2 = 0.10$). The findings highlight that widespread digital engagement produces differentiated mobility outcomes shaped by socio-economic capacity, emphasizing the need for segment-sensitive and inclusive smart tourism strategies.

Keywords: Digital adoption, Smart tourism ecosystem, techno-behavioral segmentation, TwoStep Cluster Analysis

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1. Introduction

The global tourism system has undergone profound structural and behavioral changes in the aftermath of the COVID-19 pandemic, fundamentally reshaping how tourists plan, navigate, and experience destinations [1], [2]. Accelerated digitalization, heightened risk awareness, and shifting mobility preferences have intensified behavioral heterogeneity, challenging segmentation approaches that rely primarily on static socio-demographic profiles [3]. As travel activities become increasingly mediated by digital platforms and real-time information systems, contemporary segmentation frameworks must move beyond demographic descriptors and incorporate technology-enabled behavior and mobility-oriented decision processes.

Classical tourism segmentation has traditionally emphasized socio-demographic and psychographic attributes such as age, income, and lifestyle [4]. While these approaches remain operationally useful, their explanatory power is increasingly limited in post-pandemic contexts characterized by rapid behavioral adaptation and digitally supported decision-making [5]. The pandemic accelerated the adoption of mobile applications, online booking systems, and contactless services across the travel lifecycle, making digital literacy and online engagement critical behavioral differentiators that interact with socio-economic capacity in shaping mobility choices and destination experiences [6].

The Smart Tourism Ecosystem (STE) framework provides a relevant lens for understanding this transformation by conceptualizing tourism as a socio-technical system in which data, connectivity, and digital services mediate tourist behavior and destination governance [7], [8]. Within this framework, digital technologies function not merely as enabling infrastructure but as behavioral mechanisms influencing itinerary complexity, spatial dispersion, and adaptive mobility [9]. From a spatial perspective, digitally coordinated mobility systems further reshape how tourists move within destinations, reinforcing the need to integrate behavioral–spatial analysis into segmentation research [10].

Despite these advances, empirical segmentation studies rarely integrate socio-demographic structure, digital adoption, and mobility behavior within a single data-driven framework, particularly in developing-country and post-pandemic contexts. Most existing research examines demographic heterogeneity or digital technology use in isolation, overlooking how digital capability mediates the translation of socio-economic resources into differentiated mobility outcomes.

To address this gap, this study proposes a techno-behavioral, data-driven segmentation approach using TwoStep Cluster Analysis. Drawing on a mixed-mode survey of 805 domestic tourists in a smart-destination context in Indonesia, the study identifies distinct post-pandemic tourist segments and examines how digital adoption mediates the relationship between socio-demographic attributes and mobility-oriented travel behavior. By positioning digital adoption as a central behavioral mechanism, this research advances tourism segmentation theory and provides empirically grounded insights for adaptive and inclusive smart-destination governance.

2. Methods

2.1. Research Design

This study adopts a quantitative, data-driven research design to identify post-pandemic tourist segments by integrating socio-demographic characteristics, travel behavior, and digital adoption within a Smart Tourism Ecosystem (STE) framework [6], [7]. An exploratory, unsupervised segmentation approach is implemented using TwoStep Cluster Analysis (TSCA), which is appropriate for large samples and mixed data types (categorical and continuous) [11], [12].

TSCA follows a two-stage procedure consisting of pre-clustering and hierarchical agglomeration, with the optimal number of clusters automatically determined using the Bayesian Information Criterion (BIC) and a log-likelihood distance measure [13], [14]. Cluster quality is assessed using the Silhouette Coefficient, which evaluates the balance between within-cluster cohesion and between-cluster separation [15]. Silhouette values range from −1 to 1, where values from −1.0 to 0.2 indicate poor cluster quality, values between 0.2 and 0.5 indicate fair cluster quality, and values from 0.5 to 1.0 indicate good cluster quality [15], [15].

2.2. Data Collection and Sampling Procedure

Primary data were collected through a mixed-mode survey combining on-site and online administration between June and August 2024 in Yogyakarta, Indonesia. The target population consisted of domestic tourists who had undertaken at least one leisure trip within the preceding 12 months. A stratified random sampling strategy based on gender, age group, and region of origin was applied to enhance representativeness.

On-site surveys were conducted at major tourism activity nodes, while the online questionnaire was distributed through digital travel communities. After data screening and cleaning, a total of 805 valid responses were retained for analysis. Participation was voluntary and anonymous, and no personally identifiable information was collected, in accordance with established ethical guidelines for social research [16]. A summary of respondent characteristics is presented in Table 1.

Table 1. Respondent Characteristics

Variable	Category	N	%
Number of Clusters	Automatically determined by BIC	2 clusters	Optimal solution
Gender	Male	398	49.4
	Female	407	50.6
Generational Cohort	Gen Z (1995–2015)	425	52.8
	Gen Y / Millennial (1980–1994)	328	40.7
	Gen X (1965–1979)	52	6.5
Education Level	Secondary (SMA/SMK)	261	32.4
	Undergraduate (D3/S1)	390	48.4
	Postgraduate (S2/S3)	154	19.1
Employment Status	Public sector (PNS/ASN, BUMN, govt.)	277	34.4
	Private sector	275	34.2
	Students	212	26.3
	Others	41	5.1
Monthly Income	< IDR 2 million	287	35.7
	IDR 2–5 million	171	21.2
	> IDR 5 million	347	43.1
Frequency of visits to DIY (past 12 months)	1 time	144	17.9
	2 times	163	20.2
	3 times	195	24.2
	≥4 times	303	37.6
Region of Origin	Java	321	39.9
	Sumatra	258	32.0
	Kalimantan	68	8.5
	Sulawesi	78	9.7
	Maluku & Papua	43	5.3
	Bali & Nusa Tenggara	37	4.6
Use of Online Applications	Yes	725	90.1
	No	80	9.9

2.3. Measurement and Variables

The questionnaire operationalized the conceptual framework through three groups of variables: socio-demographic characteristics, travel behavior, and digital travel behavior. Socio-demographic variables included generational cohort, gender, education level, employment status, and monthly income [17]. Travel behavior variables captured transport mode, visit frequency, length of stay, number of destinations visited, and temporal patterns of travel activities [18]. Digital travel behavior was measured through the use of online applications for navigation, booking, and travel planning [19].

Most variables were categorical and numerically coded for clustering purposes without imposing metric assumptions. In addition, one continuous variable, Itinerary Intensity (URUTAN) was included to represent trip-chain complexity and mobility intensity, defined as the total number of distinct activity and movement stages undertaken during a trip. Given the use of a log-likelihood distance measure, no variable standardization was required [13].

Overall, the measurement design follows established standards in tourism segmentation research by integrating socio-demographic structure, observable travel behavior, and digital adoption within a unified analytical framework [4], [7], [20]. By combining traditional segmentation attributes with digital engagement and mobility-related measures, the approach enables a holistic and data-driven assessment of tourist heterogeneity in post-pandemic smart tourism environments while supporting robust clustering and theoretically meaningful interpretation.

2.4. Data Analysis Porcedure

Data analysis was performed using IBM SPSS Statistics version 27. Prior to clustering, data screening was conducted to remove incomplete responses and check for extreme outliers; no severe outliers were detected. TwoStep Cluster Analysis was applied with automatic cluster determination based on the Bayesian Information Criterion (BIC) and a log-likelihood distance measure [21]. Cluster quality was evaluated using the Silhouette Coefficient. External validity was assessed using Chi-square tests for categorical variables and t-tests or ANOVA for continuous variables, particularly Itinerary Intensity (URUTAN). Robustness was further examined through split-sample validation (70% estimation; 30% validation) and sensitivity analysis based on predictor-importance thresholds. All analyses were conducted using default SPSS settings to ensure reproducibility.

3. **Results and Discussion**

3.1. TwoStep Cluster Results and Model Fit

The TwoStep Cluster Analysis (TSCA) generated an optimal two-cluster solution based on a combination of socio-demographic characteristics, travel behavior, and digital adoption variables. The number of clusters was automatically determined using the Bayesian Information Criterion (BIC) with a log-likelihood distance measure, which is appropriate for mixed categorical and continuous indicators. This criterion-based procedure minimizes researcher subjectivity and ensures analytical consistency in exploratory segmentation involving heterogeneous tourism populations. The resulting clustering solution achieved a Silhouette Coefficient of 0.32, indicating fair cluster cohesion and separation, which is considered acceptable for exploratory segmentation involving heterogeneous socio-demographic, behavioral, and technological variables. As illustrated in Figure 1, the model summary supports the automatic selection of the two-cluster solution and confirms acceptable clustering quality based on the silhouette measure of cohesion and separation.

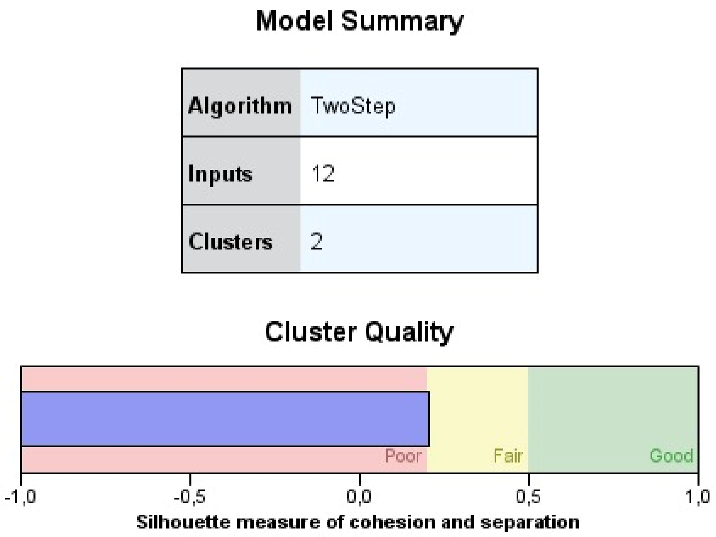

Figure 1. Model summary and cluster quality based on Silhouette's measure of cohesion and separation

The distribution of respondents across clusters is relatively balanced. Digital Leisure Travelers (DLT) constitute 56.7% of the sample (n = 457), while Budget-Conscious Digital Natives (BDN) account for 43.3% (n = 348). To assess the precision and reliability of these estimates, 95% confidence intervals were calculated for each cluster proportion. As reported in Table 2, the confidence intervals are relatively narrow (DLT: 53.3%–60.1%; BDN: 39.9%–46.7%), indicating stable estimation of segment sizes and supporting the robustness of the two-cluster solution.

Tabel 2. Cluster Distribution with 95% Confidence Intervals (N = 805)

Cluster	n	Sample Proportion (p)	95% Confidence Interval (CI)
Digital Leisure Travelers (DLT)	457	56.7%	53.3% – 60.1%
Budget-Conscious Digital Natives (BDN)	348	43.3%	39.9% – 46.7%
Total	805	100.0%	

Tabel 3. Predictor Importance from TwoStep Cluster Analysis (N = 805)

Rank	Predictor Variable	Importance (Normalized)	Interpretation
1	Monthly Income	1.00	Strongest Discriminator
2	Education Level	0.89	Very Strong
3	Generational Cohort	0.85	Very Strong
4	Use of Online Applications	0.72	Strong
5	Employment Status	0.45	Moderate
6	DIY Visit Frequency	0.38	Moderate
7	Transport Mode	0.35	Moderate
8	Stay Duration (Nights)	0.31	Moderate

9	Itinerary Intensity (URUTAN)	0.28	Moderate
10	Gender	0.15	Weak
11	Number of Destinations (Trip)	0.12	Weak
12	Trip Start/End Time	0.08	Weak

Analysis of predictor-importance diagnostics further clarifies the structure of the clustering solution. As shown in Table 3, monthly income, education level, and generational cohort exhibit the highest predictor-importance values, followed by the use of online applications. These results indicate that socio-economic capacity and digital adoption are the primary drivers of cluster formation, while behavioral variables such as itinerary intensity (URUTAN), transport mode, and visit frequency play a secondary but complementary role in refining cluster differentiation.

To examine inter-cluster distinctiveness, external validation was conducted using Chi-square tests for categorical variables and t-tests or ANOVA for continuous indicators. The results, presented in Table 4, confirm statistically significant differences between clusters across most socio-demographic, behavioral, and mobility-related variables ($p < 0.05$), with moderate to strong effect sizes for key discriminators such as income, education, and generational cohort. Variables with non-significant differences (e.g., gender, trip start time) exhibit small effect sizes, indicating limited discriminatory power and supporting the substantive coherence of the segmentation.

Taken together, the BIC-based cluster selection, acceptable silhouette value, balanced and precisely estimated cluster proportions, stable predictor-importance structure, and statistically significant inter-cluster differences indicate that the TwoStep Cluster Analysis yields a reliable and analytically valid segmentation framework. This provides a solid empirical foundation for the subsequent representation and interpretation of techno-behavioral tourist segments in Section 3.2.

Table 4. Cluster Profiles and Significance Tests (N = 805)

Validation	**Cluster 1: Digital Leisure Travelers (DLT)**	**Cluster 2: Budget-Conscious Digital Native (BDN)**	**χ^2 / ANOVA (p)**	**Cramér's V / η^2**
Generational Cohort	Gen Y 71.8%, Gen Z 17.1%, Gen X 11.1%	Gen Z 99.7%, Gen Y 0.0%, Gen X 0.3%	< 0.001	0.82
Education Level	SMA 0.4%, D3/S1 68.3%, S2/S3 31.3%	SMA 74.4%, D3/S1 22.4%, S2/S3 3.2%	< 0.001	0.79
Monthly Income	< 2 M 2.2%, 2–5 M 22.1%, > 5 M 75.7%	< 2 M 79.6%, 2–5 M 20.1%, > 5 M 0.3%	< 0.001	0.86
Employment Status	Public 56.0%, Private 34.4%, Student 5.7%, Other 3.9%	Public 6.0%, Private 33.9%, Student 53.4%, Other 6.6%	< 0.001	0.63
Gender	Male 51%, Female 49%	Male 47%, Female 53%	0.217	0.05
Transport mode	Private 19.0%; Public–route 34.1%; Public–non-route 46.8%	Private 10.1%; Public–route 39.9%; Public–non-route 50.0%	0.0017	0.126
DIY visit frequency	1× 15.1%; 2× 18.4%; 3× 23.9%; ≥4× 42.7%	1× 21.6%; 2× 22.7%; 3× 24.7%; ≥4× 31.0%	0.0035	0.130
Stay duration (nights)	Daytrip 5.9%; 1–3 nights 53.2%; >3 nights 40.9%	Daytrip 4.3%; 1–3 nights 62.4%; >3 nights 33.3%	0.0317	0.093
Number of Destinations (Trip)	1 = 3.7%, 2 = 48.4%, ≥ 3 = 47.9%	1 = 2.3%, 2 = 50.6%, ≥ 3 = 47.1%	0.471	0.04
Trip Start Time	Morning (< 09:00) 90.6%	Morning 93.7%	0.111	0.06

Trip End Time	≤ 18.00 54.5%, > 18.00 45.5%	≤ 18.00 58.9%, > 18.00 41.1%	0.210	0.04
Use of Online Applications	87.5% users, 12.5% non-users	93.4% users, 6.6% non-users	0.006	0.10
Itinerary Intensity (URUTAN)	M = 29.00 ± 8.69	M = 22.14 ± 14.85	$t(525) = 7.67$, $p < .001$	$\eta^2 = 0.10$; d = 0.58

3.2. Interpretation of Segments

The TwoStep Cluster Analysis identifies two socio-behaviorally distinct tourist segments that differ in socio-economic capacity, digital adoption, and mobility orientation. Although both segments demonstrate high levels of digital engagement, digital technologies are translated into fundamentally different mobility outcomes depending on available resources and life-stage constraints. This pattern is consistent with recent post-pandemic tourism studies emphasizing that digitalization amplifies, rather than homogenizes, behavioral heterogeneity among tourists [4].

The first segment, Digital Leisure Travelers (DLT), comprises 56.7% of the sample (n = 457) and is dominated by Millennials and higher-income Generation Z travelers with higher educational attainment and intensive use of mobile applications for navigation, booking, and real-time mobility management. This group exhibits significantly higher mobility intensity (M = 29.00; SD = 8.69), reflecting complex trip chaining and multi-destination travel within relatively short stays. Similar profiles have been identified in smart tourism research, where digitally empowered and resource-rich tourists leverage technology to support adaptive itineraries, spatial dispersion, and experience maximization [6], [7]. These patterns indicate that, for DLTs, digital technologies function as active enablers of flexible and experience-oriented mobility, allowing travelers to dynamically adjust itineraries and expand spatial exploration during their trips.

The second segment, Budget-Conscious Digital Natives (BDN), accounts for 43.3% of respondents (n = 348) and is predominantly composed of Generation Z travelers, many of whom are students or individuals with limited income capacity. Despite very high digital usage (93.4%), this segment demonstrates lower mobility intensity (M = 22.14; SD = 14.85), characterized by longer stays, fewer destinations visited, and more spatially concentrated travel. This finding aligns with prior evidence showing that digitally fluent but economically constrained tourists use technology primarily to optimize costs, reduce uncertainty, and support efficient planning rather than exploratory mobility [22]. Digital engagement among BDNs is therefore primarily instrumental, focusing on navigation, booking, and cost optimization rather than spontaneous exploration or itinerary reconfiguration.

A direct comparison between the two segments reveals a statistically significant difference in itinerary intensity ($t = 7.67$, $p < 0.001$; $\eta^2 = 0.10$). While both segments actively adopt digital technologies, DLTs convert digital capabilities into high-mobility, experience-driven travel, whereas BDNs leverage digital tools to manage efficient and economically constrained mobility. This divergence reinforces emerging segmentation literature suggesting that digital adoption acts as a mediating mechanism whose behavioral effects are conditioned by socio-economic resources rather than a uniform driver of mobility outcomes. Overall, the findings confirm that digital adoption operates as a mediating mechanism rather than a standalone determinant of tourist mobility, with socio-economic capacity shaping how digital engagement is translated into post-pandemic travel behavior in smart tourism contexts.

3.3. Robustness and Validation Results

The robustness and validity of the clustering solution were assessed using multiple internal and external validation procedures. Internal quality evaluation indicated a Silhouette Coefficient of 0.32, suggesting fair and acceptable cluster separation for exploratory segmentation involving heterogeneous populations and mixed data types. Predictor-importance diagnostics further confirmed that the cluster solution was primarily driven by socio-economic and techno-behavioral variables, particularly monthly income, education level, generational cohort, and use of online applications.

External validation was conducted using Chi-square tests for categorical variables and independent-samples t-tests for continuous indicators. The results demonstrate statistically significant differences between clusters across most socio-demographic, behavioral, and mobility-related variables ($p < 0.05$), including itinerary intensity, transport mode, visit frequency, length of stay, and digital application usage. Effect size measures (Cramér's V and η^2) indicate moderate to strong substantive differences for key discriminating variables, supporting the interpretability of the segment profiles.

To further assess robustness, a sensitivity analysis was performed by excluding variables with low predictor-importance values (< 0.60). The resulting cluster structure remained stable in terms of both composition and relative size. In addition, a split-sample validation (70% estimation and 30% validation) produced consistent cluster proportions with deviations of less than ±3%, confirming the stability and reproducibility of the two-cluster solution. Overall, these validation procedures provide strong support for the reliability of the segmentation results and their suitability for subsequent interpretation and policy-relevant analysis in smart tourism contexts.

3.4 Disscusion

The findings identify two techno-behavioral tourist segments, Digital Leisure Travelers (DLT) and Budget-Conscious Digital Natives (BDN) and demonstrate that digital adoption operates as a mediating mechanism linking socio-demographic structure and mobility-oriented travel behavior. This result extends classical tourism segmentation by showing that socio-economic resources shape how digital engagement is translated into differentiated mobility outcomes rather than functioning solely as descriptive classifiers [4]. Income, education, and generational cohort emerge as key conditioning factors because they influence travelers' functional capacity to convert digital access into flexible, exploratory, and multi-destination travel, while resource constraints limit the spatial expansion of mobility despite high digital fluency.

From a Smart Tourism Ecosystem perspective, technology simultaneously functions as enabling infrastructure and behavioral mediator [6], [7]. Digital platforms provide real-time information, booking systems, and AI-driven decision-support tools that shape itinerary formation and visitor flow management [23]. However, the translation of digital engagement into actual spatial mobility also depends on supporting mobility infrastructures such as integrated transport systems and destination accessibility [24]. Consistent with spatial movement research, mobility outcomes reflect the interaction between technological capability, spatial constraints, and resource availability rather than digital access alone [25]. The coexistence of digitally enabled high-mobility travelers and digitally fluent but mobility-constrained travelers therefore illustrates that technological diffusion does not automatically generate homogeneous tourism behaviors.

Integrating a behavioral–spatial perspective further suggests that mobility intensity and trip chaining are outcomes of resource organization and activity constraints rather than preferences alone. Analytically, the segmentation results support a moderated mediation structure in which digital adoption mediates the relationship between socio-demographic attributes and travel behavior, while the conversion of digital capability into mobility intensity is conditioned by economic, infrastructural, and life-stage factors. This conceptualization reframes segmentation as a dynamic socio-technical process and strengthens the theoretical foundation for data-driven techno-behavioral segmentation in post-pandemic tourism systems.

From a destination management perspective, the segmentation results provide actionable guidance for designing inclusive smart tourism strategies. Although digital engagement is widespread across segments, its mobility benefits remain unevenly distributed. Digitally empowered high-mobility travelers benefit from interoperable real-time systems that support multi-destination movement, whereas economically constrained but digitally fluent travelers require affordable transport integration, transparent pricing information, and reliable digital navigation support to ensure equitable physical accessibility. Aligning digital service design, mobility infrastructure, and governance mechanisms with heterogeneous traveler capacities is therefore essential to prevent technology-enabled exclusion and to translate digital innovation into inclusive mobility outcomes.

4. Conclusion

This Building on the techno-behavioral mechanisms examined in this study, post-pandemic tourist heterogeneity is shown to arise from the interaction between socio-demographic capacity, digital adoption, and mobility-oriented travel behavior within the Smart Tourism Ecosystem framework. Using survey data from 805 domestic tourists in Yogyakarta, Indonesia, and applying TwoStep Cluster Analysis, the study identified two empirically distinct segments, Digital Leisure Travelers (DLT) and Budget-Conscious Digital Natives (BDN), which differ primarily in socio-economic capacity and mobility orientation rather than in access to digital technologies.

The findings demonstrate that digital engagement has become a baseline condition of contemporary tourism, while its behavioral and spatial consequences remain stratified by income, education, and life-stage constraints. Digital Leisure Travelers translate digital adoption into flexible, high-intensity, and multi-destination mobility, whereas Budget-Conscious Digital Natives utilize similar digital tools mainly to support cost-efficient and spatially concentrated travel. These results confirm that digital adoption functions as a mediating mechanism linking socio-demographic structure and travel behavior, rather than operating as a standalone determinant of tourist differentiation.

The study contributes to tourism segmentation research by advancing a data-driven techno-behavioral segmentation perspective that integrates digital engagement into the behavioral–spatial paradigm. By demonstrating how socio-economic capacity conditions the translation of digital engagement into differentiated mobility outcomes, the research extends Smart Tourism Ecosystem theory beyond technological availability toward the unequal behavioral realization of digital access. This perspective helps explain why widespread digital connectivity does not necessarily generate homogeneous mobility patterns in post-pandemic destinations.

Several limitations should be acknowledged. The analysis focuses on a single destination and domestic tourists, limiting broader generalization across geographic contexts and international travel markets. In addition, the cross-sectional design constrains inference regarding temporal dynamics and causal mechanisms. Future research should extend this framework to multi-destination and cross-country contexts, employ longitudinal approaches, and incorporate psychographic and motivational constructs to further explain how digital adoption translates into differentiated mobility behavior over time.

Overall, this study highlights that post-pandemic smart tourism is characterized not by unequal access to digital technologies, but by unequal capacity to convert digital engagement into mobility and experiential outcomes. Recognizing this distinction is essential for advancing segmentation theory and for guiding the development of inclusive, segment-sensitive smart tourism strategies capable of accommodating heterogeneous traveler capacities.

Declaration of AI and AI assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT for language editing and structural improvement of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication. All data analysis and interpretation were performed independently by the author(s).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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