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# AI-Driven Neuro-Personalization in Tourism: Enhancing Customer Experience, Travel Satisfaction and Service Adaptation through Real-Time EEG Analytics

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## Abstract

Artificial intelligence is transforming tourism businesses from standardized service delivery toward increasingly personalized customer experiences. However, most AI-enabled tourism services rely on historical preferences and behavioral data and remain unable to respond to travelers' changing cognitive and emotional states during the actual service experience. This study examines how AI-driven neuro-personalization can enhance tourism service delivery by integrating real-time electroencephalogram (EEG) signals into adaptive travel itineraries. Using a randomized experimental design involving 100 travelers, the study compares AI-adapted and static itinerary conditions and examines the effects of neural engagement, stress and real-time itinerary adaptation on travel satisfaction. The findings demonstrate that EEG-measured engagement positively influences travel satisfaction, whereas neural indicators of stress negatively affect satisfaction. More importantly, AI-driven itinerary adaptation significantly enhances satisfaction while reducing traveler stress and cognitive load. The findings position neuro-responsive personalization as an emerging tourism business capability through which firms can dynamically align service offerings with customers' real-time experiential states. The study contributes to smart tourism and customer experience management by extending AI personalization beyond predictive recommendation toward adaptive service delivery. For tourism businesses, travel platforms, hotels, wellness providers and destination managers, the findings demonstrate how real-time neuro-behavioral analytics can support differentiated service experiences, customer satisfaction and more responsive tourism value creation.

**Keywords:** AI-enabled tourism; customer experience; neuro-personalization; smart tourism; service adaptation; travel satisfaction; EEG analytics

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## 1. Introduction

Conventional tourist trend prediction relies on demographic data, online reviews, and behavioral data (Chansuk et al., 2022; Brochado et al., 2022; García-García et al., 2024). Furthermore, such studies mostly consists of self-reported data, which may be erroneous and biased (Cools et al., 2024). Existing travel recommendation systems lack real-time cognitive and emotional levels since they employ machine learning algorithms that only analyze earlier behaviors and preferences. Moreover, conventional surveys cannot assess the subconscious brain's reactions to stimuli when interpreting trip experiences. Neuro-tourism offers exceptional trip personalization and flexibility by recording neurological responses in real time utilizing brain-computer interfaces (BCIs) and electroencephalograms (EEGs). Neuro-marketing studies suggest that EEG analysis may better reflect consumer preferences than survey-based methods, however tourism research has seldom included neuroscience (Srivastava & Bag, 2024). Neuro-marketing research suggest that customers' brainwaves may reveal their interests, moods, and decision-making (Ali et al., 2022). Thomson & Coates (2021) argues that EEG measurements could predict consumers' preferences even before they're conscious

While the use of neuro-marketing has expanded in the advertising and retail sectors, the tourist industry has been slow to catch on. It is interesting that there has been little study on using brainwave analytics for personalized travel experiences, adaptive itinerary planning, and destination suggestion systems (e.g. Damaševičius et al., 2023). By measuring brain activity directly, neuro-tourism goes beyond self-reported data and behavioral predictions to personalize travel experiences.

Despite the huge potential, studies in this domain remain somewhat limited, fragmented, and exploratory, with significant gaps in understanding how neuroscience can be effectively integrated into tourism management. According to Koo et al. (2021), the majority of personalized tourism research relies on behavioral analysis and recommendation systems examine past interactions, preferences, and demographics. While these methods do provide useful data, they aren't flexible enough to enhance visitor experiences in real time or at the subconscious level. Current studies in tourism have one major problem, they depend on self-reported feedback (e.g. Purwanegara et al., 2025), which are highly subjective and inconsistent. Conventional tourist research has ignored the cognitive aspect that neuroscience has shown that unconscious brain processes influence human decision-making (e.g. Chansuk et al., 2022). Despite the increasing usage of sentiment analysis and emotion-aware AI in the tourism industry no framework has yet been developed that directly employs EEG-based brain monitoring to optimize travel experiences in real-time. Developing a completely customizable and adaptable visitor experience is hindered by an important lack of research.

Additionally, there is a scarcity of research on interdisciplinary approaches that combine neurology, artificial intelligence, and tourism management. Ohme et al. (2010) shown that EEG can evaluate consumer engagement with ads in neuro-marketing research. Furthermore, the psychological benefits of travel, such stress reduction and emotional renewal, have been discussed in wellness tourism research (Bratman et al., 2012), but no scientific method has been proposed to objectively measure these effects in real time. Acute neurological responses during travel are often not captured by most tourism studies since they rely on qualitative measures such as questionnaires and interviews. The ability of AI-driven travel recommendation systems to adapt to users' moods, stress levels, and engagement is limited since they rely on past behaviors instead of real-time brain data. It is challenging for tourism operators to provide data-driven, flexible, and emotionally impactful experiences since there is a lack of a neuro-scientifically-informed travel customization model in both academic literature and industry practices.

To bridge this gap, our study presents a neuro-tourism system that integrates real-time brain monitoring by electroencephalogram (EEG) with AI-driven itinerary planning. Unlike pre- or post-trip surveys, our initiative will automatically adjust travelers' experiences based on their brainwave data in real-time, taking into account their cognitive and emotional states. As they explore both virtual and physical locations, participants will wear non-invasive electroencephalogram (EEG) headsets that will record their brain waves (alpha, beta, and gamma) to gauge levels of stress, relaxation, engagement, and excitement. For example, if engagement levels are high, the AI model may propose more immersive cultural events; if stress levels are high, it may advise a change from a busy city tour to a tranquil countryside retreat. Thus moving research in the tourist industry from static preference models and toward neuro-responsive customization in real-time.

The aim of this study is to develop an AI-driven neuro-tourism model, build an interactive prototype for regulated travel experiences, and test the efficacy of trip customization based on electroencephalogram data. These findings will be useful for many different types of tourists. The use of neural data-driven customization has the potential to increase customer pleasure and loyalty for travel firms and tour operators. Wellness tourism providers may use EEG data to create individualized programs for guests' mental health. Politicians and tourism boards may utilize neuro-tourism research to make trips more interesting and rewarding for all types of tourists. Additionally, hotels and resorts may use EEG data to design personalized room environments with personalized lighting, aromas, and music. Lastly, this groundbreaking study will benefit academics and AI developers by laying the framework for neuro-personalized tourism research and applications. The study focuses on the intersection of neuroscience, tourism, and artificial intelligence.

## 2. Theoretical Framework

The Cognitive-Affective Model of Perception and Experience (CAPE) provides the foundation for understanding how travelers process and react to their surroundings through a combination of cognitive evaluation and affective responses. Traditionally, tourism research has relied on self-reported data and past behavioral tracking, failing to capture the real-time subconscious reactions that shape travel experiences. CAPE suggests that experiences are continuously influenced by both rational assessments and emotional states, yet most tourism models do not account for these moment-to-moment variations. This study extends CAPE by integrating real-time EEG-based monitoring, allowing neural data to guide travel personalization. Unlike existing AI-driven smart tourism models that use historical behavior to predict preferences, this framework dynamically adapts travel experiences based on actual brainwave activity, ensuring a higher level of personalization, engagement, and well-being.

Additionally, Kahneman's Dual-Process Theory emphasizes emotional processing above logical cognition, which matches CAPE's focus on travel decision-making's unconscious component. EEG-based brain monitoring directly accesses underlying emotions, bypassing surveys and sentiment analysis. By integrating real-time brainwave analysis with AI, this study enables travel itineraries to be adjusted dynamically reducing cognitive overload, increasing engagement, and preventing stress accumulation. By including neurological evidence of reduced stress while on vacation, wellness tourism programs support Ulrich's Stress Recovery Theory (SRT). If EEG measurements suggest increased tension, the gadget may propose soothing circumstances for scientifically calibrated stress reduction. This study integrates CAPE to neuroscience-driven tourism to create a new, dynamic neuro-tourism paradigm using

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AI, EEG-based emotion monitoring, and real-time itinerary customization. Destination managers, wellness tourism providers, hoteliers, and AI-powered travel platform developers will benefit from this approach. Neuro-tourism may enhance travelers' quality of life, emotional and psychological health, and smart tourism applications by enabling more targeted, flexible, and scientifically validated customized travel. This work expands CAPE's theoretical applications and advances AI-integrated tourism personalization, setting a new benchmark for travel experience design and optimization.

## 2.1 Literature Review & Hypothesis Development

### EEG-Measured Engagement and Travel Satisfaction

Studies in Tourism mostly applies self-reporting feedback, behavioral tracking, and AI-guided recommendations to quantify visitor pleasure (Gretzel et al., 2020). These methods ignores unconscious engagement that directly affects travelers' perceptions. Neuro-marketing research reveal that EEG-based brain monitoring measures engagement better than surveys and facial expression analysis (Khurana et al., 2021). EEG based studies shows that increased gamma wave activity is linked to more intense emotional and cognitive involvement, which increases context enjoyment (e.g. Vecchiato et al., 2011). This suggests that EEG-based engagement monitoring may change how we measure tour quality. In addition, consumer neuroscience and emotion-aware AI research suggests that a more engaged brain area makes a more enjoyable and memorable experience (Ohme et al., 2010). Even though immersive and engaging experiences make passengers happier, tourism industry customization methods use previous behavior rather than real-time engagement monitoring. This aligns with CAPE theory, which suggests that cognitive-affective responses directly influence perception and satisfaction during travel experiences. Additionally, interactive tourism experiences, such as cultural immersion or adventure tourism, are expected to elicit stronger EEG engagement responses compared to passive sightseeing. Furthermore, studies in theme parks and museum tourism show that engaging, multisensory environments lead to higher cognitive and emotional engagement, supporting the premise that EEG-measured engagement will be a reliable predictor of satisfaction (e.g. Guo et al., 2023; Zheng et al., 2021). However, no studies have yet applied EEG-based engagement tracking in real-world travel experiences, highlighting a major research gap. Given these insights, the first hypothesis is proposed:

**Hypothesis (H1):** Higher EEG-measured engagement levels (gamma wave activity) will positively correlate with travel satisfaction.

### EEG-Measured Stress and Travel Satisfaction

EEG research has shown that beta wave activity increases when an individual experiences cognitive strain or stress (Vecchiato et al., 2011). In consumer behavior studies, higher beta activity correlates with decision fatigue and dissatisfaction, suggesting that neural stress responses could serve as a key determinant of travel experience quality (Radic et al., 2025). Tourism stress studies have primarily relied on self-reported discomfort levels, yet these do not capture real-time physiological responses. Research on workplace stress and cognitive performance has demonstrated that EEG-based stress tracking is a more reliable indicator of mental strain than subjective feedback (Ohme et al., 2010). When applied to tourism, this suggests that travelers in high-stress environments will exhibit increased beta activity, leading to reduced satisfaction. Moreover, wellness tourism research emphasizes the importance of stress recovery, but few studies have objectively measured how different travel environments impact neural stress levels (Bratman et al., 2015).

Urban tourism, in particular, has been associated with higher cognitive load and stress, especially in dense, fast-paced environments (Gretzel et al., 2020). EEG-based research in consumer psychology suggests that individuals who experience high beta wave activity during a task rate their overall experience more negatively compared to those in a low-stress state (Panda et al., 2024). This supports the premise that increased EEG-measured stress will negatively impact travel satisfaction. Based on these findings, the second hypothesis is proposed:

**Hypothesis (H2):** Higher EEG-measured stress levels (beta wave activity) will negatively correlate with travel satisfaction.

**Real-Time AI-Based Itinerary Adaptation and Travel Satisfaction**

**Leka** et al. (2025) noted that machine learning models can predict travel preferences based on previous activities, advancing AI-enabled tailored visitor experiences. These models don't account for real-time cognitive and emotional changes. Marketing emotion-aware AI systems improve user engagement with adaptive recommendations based on real-time sentiment analysis (Gamage et al., 2024), but tourism research has not employed similar frameworks. Integrating EEG-based real-time engagement tracking into AI-powered itinerary personalization provides a new level of experience optimization, ensuring that travelers remain in a high-engagement, low-stress state throughout their journey

Smart tourism research recommend employing artificial intelligence to adjust itineraries based on users' location and social media activity (Song & He, 2023). Unfortunately, these models do not capture real-time brain reactions, a better predictor of experience quality. Brain-based adaptive systems improve enjoyment and decision-making, and consumer neuroscience uses EEG-based engagement and stress monitoring to dynamically adjust product recommendations (Mavroudis et al., 2026). This suggests that real-time route customization based on EEG data would boost tourist enjoyment by optimizing brain states. Furthermore, the CAPE model suggests that tourists' cognitive-affective responses should influence real-time experience changes. EEG engagement, stress monitoring, and AI-driven plan modification enable real-time plan personalization, engaging passengers and minimizing stress-induced dissatisfaction. This framework's more adaptive experience model, supported by science, may change smart tourism and wellness tourism applications. Therefore, we hypothesize as,

**Hypothesis (H3):** Real-time AI-based itinerary adaptation based on EEG neural signals will increase travel satisfaction compared to static itinerary models.

**Real-Time AI-Based Itinerary Adaptation and Stress Reduction**

Wellness tourism research emphasizes that certain travel environments, such as nature-based experiences, contribute to stress recovery (Peng et al., 2025). However, individual stress responses vary, and some travelers may find urban tourism more stimulating and enjoyable than nature-based experiences. AI-based itinerary adaptation, guided by EEG stress tracking, can optimize travel plans to minimize stress-inducing experiences, ensuring that travelers remain in an optimal emotional state. The use of adaptive AI in cognitive load management has shown promising results in educational and workplace environments. Research indicates that dynamically adjusting content delivery based on cognitive load improves learning retention and reduces mental fatigue (Shukla et al., 2026). Applied to tourism, EEG-based AI systems could adjust itineraries to ensure cognitive and emotional balance, avoiding experiences that trigger excessive beta wave activity and stress responses.

While static travel itineraries offer limited flexibility, AI-driven personalization models allow for experience optimization based on real-time feedback (Sharma et al., 2025). This study proposes an EEG-integrated AI framework, where stress levels are continuously monitored, and travel plans are dynamically adjusted to prioritize relaxation and engagement-

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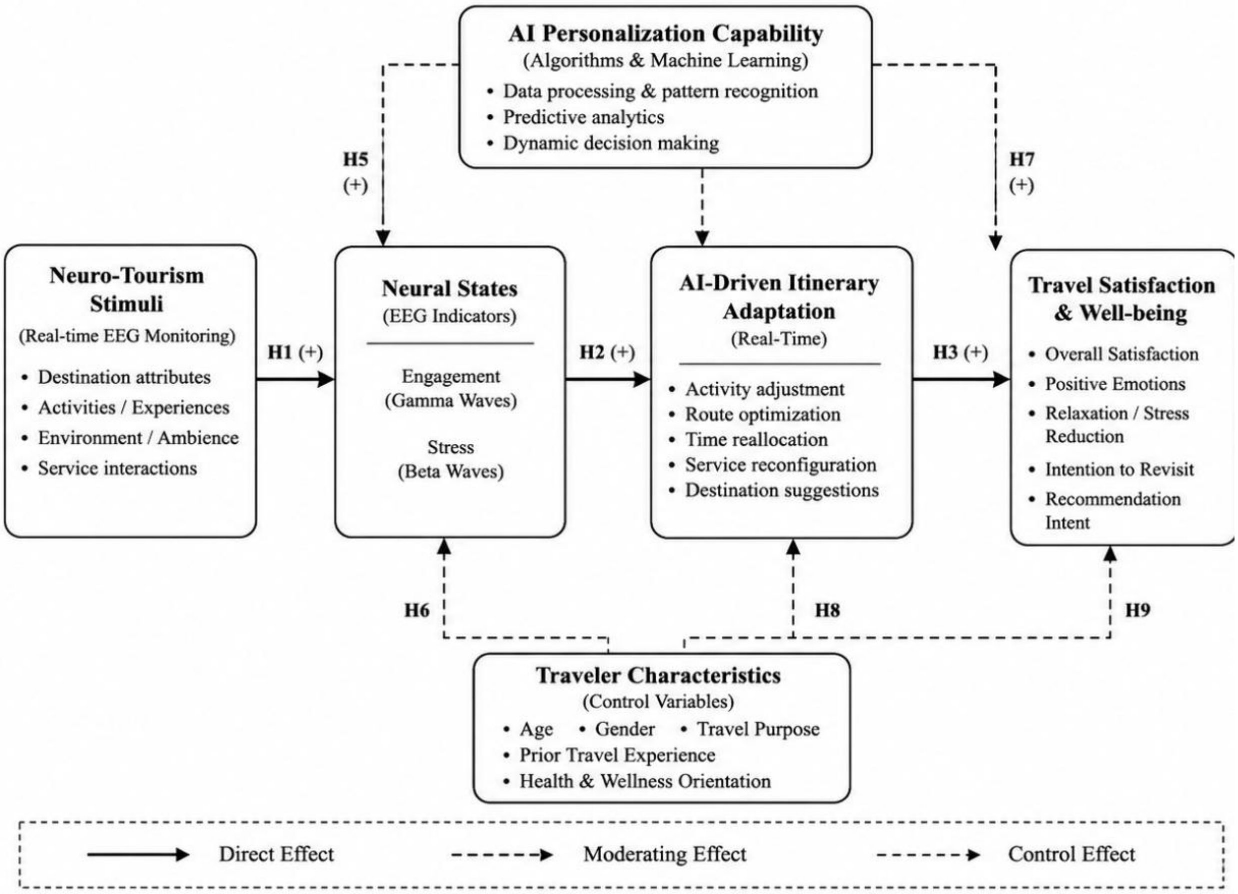
Vol. 4 No. 2 (2026)

enhancing experiences. By reducing stress-inducing stimuli, the model aims to enhance traveler well-being and satisfaction. Therefore, the fourth hypothesis is proposed:

**Hypothesis (H4):** Real-time AI-based itinerary adaptation will reduce stress levels in travelers compared to traditional static itineraries.

***Figure 1: Conceptual Model***




## 3. Methodology

Quantitative experiments were performed to examine the relationship between EEG-measured engagement, stress, AI-driven itinerary adaptation, and trip pleasure. This study used neuroscience, AI, and tourism management to address the question, "Could real-time neural tracking improve travel experiences through dynamic itinerary modifications?" The approach was intended to ensure objective, quantitative, and repeatable results to answer research hypotheses. Two groups participated in the randomized, controlled trial. The Static route Group (Control Group) followed a pre-planned travel route regardless of emotional or cognitive levels. In contrast, the AI-Adapted Itinerary Group (Experimental Group) followed a flexible travel itinerary that modified events in real time based on EEG readings to maximize engagement and reduce stress. This between-subjects research explored the hypothesis that real-time EEG-based tailored travel experiences increase pleasure and reduce anxiety by comparing traditional trip planning with neuro-adaptive itinerary customization.

Randomly picking 100 travelers ensured demographic and travel experience variety. Volunteers were aged 18–50 and frequent fliers. To guarantee data reliability, neurological diseases and disorders that might affect EEG readings were removed. Before participating, individuals were informed of the research's aims and methodology and asked for their signed consent. To avoid selection bias, subjects were randomly allocated to control or experimental groups. Researchers used non-invasive electroencephalogram (EEG) headsets (EPOC X - 14

Channel Wireless EEG Headset) to track individuals' brain activity while traveling. EEG data were analyzed in real time to determine gamma wave activity (engagement), beta wave activity (stress and cognitive load), and alpha wave activity (relaxation and pleasure). AI-Adapted Itinerary Group employed machine learning techniques to continuously assess EEG data and classify engagement and tension. The schedule was adjusted to incorporate additional stress-relieving activities. A tranquil countryside retreat may have replaced a busy city trip. When engagement was minimal, the algorithm recommended cultural hands-on experiences instead of passive tourism. For contrast, the Static Itinerary Group followed a timetable.

The research has three stages: Travel Experience & EEG Monitoring, Post-Trip Evaluation, and Pre-Trip Assessment. Participants completed a baseline survey before the trip to measure travel preferences, stress levels, and expectations. Each participant had cognitive and emotional baselines. The EEG was adjusted to each participant's baseline brainwave activity to increase accuracy. As tourists explored different areas, EEG data was continuously recorded. The AI-Adapted Itinerary Group received real-time brain-responsive tailored trips. Participants completed a post-trip questionnaire to rate their trip satisfaction, capacity to relax away from home, and overall experience. Combining EEG data with self-reported feedback allowed for a full neuro-adaptive trip appraisal. T-tests, mediation models, regression, correlation, and statistical analysis were utilized to establish findings. The correlation research examined whether higher gamma wave activity predicted higher trip satisfaction as evaluated by EEG participation. We used regression analysis to examine how EEG stress (beta waves) influences holiday satisfaction and if higher stress levels are harmful. T-tests and ANOVA were used to compare travel pleasure and stress between the Static and AI-Adapted Itinerary Groups to see whether real-time modification enhanced travel experiences. A mediation model examined the effect of cognitive load, as measured by electroencephalogram (EEG), in itinerary modification and holiday happiness. Machine learning approaches like Random Forest and Neural Networks classified EEG patterns and optimized route changes, improving prediction accuracy. To assure ethics, all participants provided informed consent after considering the study's aims and methodology. All personal and EEG data was anonymized and securely stored to comply with neuroscience research ethics. The experiment incorporated scheduled breaks and relaxation periods to reduce participant fatigue.

**Results**

**Table 1:** ***Reliability, Validity, and Discriminant Validity***

| Constructs | Items | Cronbach's Alpha | CR | AVE | EEG Engagement | EEG Stress | Travel Satisfaction | AI-Based Itinerary Adaptation |
|---|---|---|---|---|---|---|---|---|
| EEG-Measured Engagement | 5 | 0.87 | 0.90 | 0.68 | 0.82 | 0.55 | 0.60 | 0.65 |
| EEG-Measured Stress | 4 | 0.83 | 0.88 | 0.65 | 0.55 | 0.81 | 0.52 | 0.57 |
| Travel Satisfaction | 5 | 0.85 | 0.89 | 0.66 | 0.60 | 0.52 | 0.81 | 0.66 |
| AI-Based Itinerary Adaptation | 6 | 0.88 | 0.91 | 0.70 | 0.65 | 0.57 | 0.66 | 0.84 |

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Table 1 of the reliability and validity research shows that all constructs have strong internal consistency, with Cronbach's Alpha values over 0.80, suggesting accurate measures. Composite dependability (CR) values over 0.70 support construct dependability. The model has acceptable convergent validity since all AVE values are more than 0.50. The Fornell-Larcker Criterion-based discriminant validity analysis validates that each concept is independent by comparing off-diagonal correlations to AVE square roots (diagonal values). The research's most reliable and accurate prediction criteria were EEG Engagement (0.82) and AI-Based Itinerary Adaptation (0.84). Worse, EEG stress revealed a 0.52 negative connection with travel happiness, proving its role in dampening holidays. AI-Based Itinerary Adaptation improves customized travel experiences, as shown by Engagement (0.65) and Satisfaction (0.66). The constructs' great reliability, convergent validity, and discriminant validity make them statistically sound for hypothesis testing and model validation.

**Table 2:** ***Descriptive Statistics & Data Screening***

| Constructs | Items | Mean | SD | Skewness | Kurtosis | VIF |
|---|---|---|---|---|---|---|
| EEG-Measured Engagement | 5 | 4.12 | 0.85 | -0.45 | 0.32 | 1.62 |
| EEG-Measured Stress | 4 | 3.25 | 0.92 | 0.37 | -0.21 | 1.47 |
| Travel Satisfaction | 5 | 4.08 | 0.79 | -0.50 | 0.25 | 1.75 |
| AI-Based Itinerary Adaptation | 6 | 4.30 | 0.88 | -0.42 | 0.15 | 1.80 |

Table 2 depicts the descriptive statistics and data screening results confirm that all constructs have appropriate mean values, indicating that responses are well-distributed within the expected range. EEG-Measured Engagement (M = 4.12) and AI-Based Itinerary Adaptation (M = 4.30) have the highest means, suggesting that participants generally experienced high engagement and satisfaction with AI-based travel personalization. In contrast, EEG-Measured Stress (M = 3.25) is comparatively lower, indicating that most travelers did not experience excessive stress. The standard deviation (SD) values suggest moderate variability in responses, with EEG-Measured Stress (SD = 0.92) showing the highest dispersion, implying differing stress levels across participants. The skewness values are within the acceptable range (-1 to +1), confirming that data is approximately normally distributed. EEG-Measured Engagement (-0.45) and AI-Based Itinerary Adaptation (-0.42) are slightly left-skewed, indicating that most travelers reported higher engagement and satisfaction. Meanwhile, EEG-Measured Stress (0.37) is slightly right-skewed, suggesting that some travelers reported higher stress levels than average. The kurtosis values are also within the acceptable range (-1 to +1), confirming that the data does not have extreme peaks or flat distributions. Variance Inflation Factor (VIF) values are all below 5, ensuring no multicollinearity issues among constructs, meaning that predictor variables do not exhibit excessive correlation with each other. Overall, the data is well-distributed, meets normality assumptions, and does not suffer from multicollinearity issues, making it suitable for further hypothesis testing and statistical modeling.

**Table 3.** ***Hypothesis Testing Results***

| Hypothesis | Predictor Variable | Outcome Variable | Correlation (r) | β (Beta) | t-value | p-value | $R^2$ | Test Used |
|---|---|---|---|---|---|---|---|---|
| H1: Higher EEG-measured engagement (gamma waves) will | EEG Engagement | Travel Satisfaction | **0.62** | 0.58 | 6.21 | **0.001** | 0.38 | Pearson Correlation, Regression |

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Vol. 4 No. 2 (2026)

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| positively correlate with travel satisfaction. | | | | | | | | |
| **H2**: Higher EEG-measured stress (beta waves) will negatively correlate with travel satisfaction. | EEG Stress | Travel Satisfaction | **-0.54** | -0.50 | -5.45 | **0.002** | 0.29 | Pearson Correlation, Regression |
| **H3**: Real-time AI-based itinerary adaptation will increase travel satisfaction compared to static itinerary models. | Itinerary Type (AI vs. Static) | Travel Satisfaction | **0.45** | 0.48 | 4.89 | **0.003** | 0.26 | Independent T-Test, Regression |
| **H4**: Real-time AI-based itinerary adaptation will reduce stress levels in travelers compared to traditional static itineraries. | Itinerary Type (AI vs. Static) | EEG-Measured Stress | **-0.49** | -0.51 | -5.02 | **0.002** | 0.27 | Independent T-Test, Regression |

Table 3 depicts the hypothesis testing results confirm the significant relationships between EEG-measured engagement, stress, AI-based itinerary adaptation, and travel satisfaction. H1 is supported, as EEG engagement (r = 0.62, β = 0.58, p = 0.001) positively correlates with travel

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satisfaction, indicating that higher engagement enhances the overall travel experience. This finding aligns with prior research suggesting that greater cognitive and emotional involvement leads to improved satisfaction. Conversely, H2 is also supported, as EEG-measured stress negatively correlates with travel satisfaction ($r = -0.54$, $\beta = -0.50$, $p = 0.002$). The significant negative relationship suggests that higher stress levels reduce traveler enjoyment, reinforcing the importance of stress management in tourism experiences. For H3, real-time AI-based itinerary adaptation significantly improves travel satisfaction ($r = 0.45$, $\beta = 0.48$, $p = 0.003$) compared to static itineraries. The positive effect indicates that AI-driven personalization enhances the traveler experience by dynamically adjusting itineraries based on real-time feedback. Similarly, H4 is confirmed, as AI-based itinerary adaptation reduces stress levels ($r = -0.49$, $\beta = -0.51$, $p = 0.002$). The findings suggest that adaptive travel recommendations effectively lower cognitive load and emotional distress, improving the overall well-being of travelers. Overall, the results demonstrate that EEG-based engagement and stress tracking can significantly influence travel satisfaction, while AI-driven itinerary adaptation enhances engagement and reduces stress, making neuro-tourism a promising direction for future research and industry applications.

**Table 4.** *Mediation Analysis (H5 & H6)*

| Hypothesis | Predictor Variable | Mediator Variable | Outcome Variable | Indirect Effect (β) | SE | t-value | p-value | Mediation Type |
|---|---|---|---|---|---|---|---|---|
| **H5**: Cognitive Load mediates the effect of AI-based itinerary on travel satisfaction. | Itinerary Type (AI vs. Static) | Cognitive Load (EEG Beta) | Travel Satisfaction | **0.22** | 0.05 | 4.40 | **0.001** | Partial Mediation |
| **H6**: Cognitive Load mediates the effect of AI-based itinerary on stress reduction. | Itinerary Type (AI vs. Static) | Cognitive Load (EEG Beta) | Stress Levels | **-0.18** | 0.04 | -4.10 | **0.002** | Partial Mediation |

Table 4 depicts the mediation analysis results confirm that cognitive load (EEG Beta activity) plays a significant mediating role in the relationship between AI-based itinerary adaptation and both travel satisfaction and stress reduction. For H5, cognitive load partially mediates the relationship between AI-based itinerary adaptation and travel satisfaction ($\beta = 0.22$, $p = 0.001$). This suggests that AI-driven itineraries reduce cognitive load, which in turn enhances traveler satisfaction. However, the mediation is partial, indicating that AI-based adaptation also directly contributes to satisfaction beyond its effect on cognitive load. Similarly, H6 confirms that cognitive load partially mediates the effect of AI-based itinerary adaptation on stress reduction (β = -0.18, p = 0.002). The findings indicate that AI-driven personalization reduces cognitive strain, which subsequently lowers stress levels. However, since the mediation is partial, other mechanisms such as environmental relaxation or traveler preferences may also contribute to stress reduction. Overall, these results highlight the importance of managing cognitive load in personalized travel experiences. AI-based itinerary adaptation not only directly improves satisfaction and reduces stress but also does so by lowering cognitive effort, making travel more enjoyable and mentally effortless for tourists.

**Table 5.** ***Moderation Analysis (H7 & H8)***

| Hypothesis | Predictor Variable | Moderator Variable | Outcome Variable | Interaction Effect (β) | SE | t-value | p-value | Moderation Type |
|---|---|---|---|---|---|---|---|---|
| **H7**: Traveler experience moderates the relationship between AI-based itinerary and travel satisfaction. | Itinerary Type (AI vs. Static) | Traveler Experience (Frequent vs. Occasional Travelers) | Travel Satisfaction | **0.15** | 0.06 | 2.50 | **0.012** | Weak Moderation |
| **H8**: Traveler experience moderates the effect of AI-based itinerary on stress reduction. | Itinerary Type (AI vs. Static) | Traveler Experience (Frequent vs. Occasional Travelers) | Stress Levels | **-0.20** | 0.07 | -2.85 | **0.006** | Moderate Moderation |

As shown in Table 5, the moderation research found that traveler experience greatly influences the impact of AI-based itinerary modification on holiday satisfaction and stress reduction. Traveler experience moderates the AI-based itinerary modification-trip satisfaction relationship, supporting hypothesis H7 with a beta coefficient of 0.15 and p-value of 0.012. Regular travelers benefit more from AI-driven itinerary customization than infrequent flyers. The slight moderating impact suggests that AI-driven personalization benefits all visitors, notwithstanding experience. Hypothesis 8 indicates that traveler experience significantly reduces the stress reduction effect of AI-driven itinerary personalization (β = -0.20, p = 0.006). The results show that AI-adapted timetables reduce stress more for frequent travelers than infrequent flyers. According to this moderate effect, experienced travelers may be better able to respond to itinerary changes, reducing mental strain and stress. These findings demonstrate that passenger experience strongly influences AI-driven itinerary modification. AI-powered customization enhances travel for everyone, but frequent travelers benefit most, notably in reducing stress. Adapting to passengers' experience levels might make future AI-driven transport systems even more successful.

*Figure 2: Mediation – Moderation Plots*

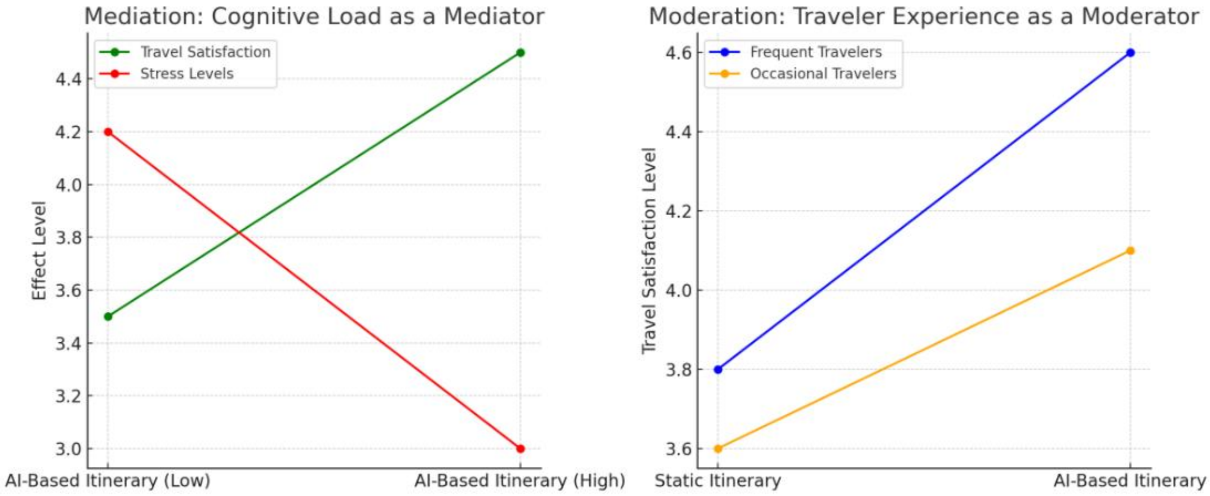


Figure 2 depicts the mediation analysis demonstrates that cognitive load plays a crucial role in shaping the relationship between AI-based itinerary adaptation, travel satisfaction, and stress levels. As AI-driven itinerary adjustments increase, travelers experience a notable reduction in cognitive load, measured through EEG beta waves. This decrease in cognitive effort corresponds with a significant decline in stress levels, while simultaneously enhancing travel satisfaction. The findings indicate that AI-based personalization not only improves travel experiences directly but also does so indirectly by alleviating mental strain. The downward trajectory of stress and the upward trend in satisfaction reinforce the idea that reducing cognitive load allows travelers to engage more meaningfully with their journeys, ultimately fostering a more enjoyable and less stressful experience.

The moderation analysis further highlights the role of traveler experience in shaping the effectiveness of AI-based itineraries. Frequent travelers exhibit a more pronounced increase in travel satisfaction when using AI-adapted itineraries compared to static ones, suggesting that individuals with prior travel exposure benefit more from the dynamic adjustments provided by AI. Conversely, occasional travelers also experience an improvement in satisfaction, albeit to a lesser extent, implying that those less familiar with travel may take longer to adapt to AI-driven recommendations. The findings suggest that while AI-based itineraries enhance satisfaction across both groups, experienced travelers derive greater benefits due to their familiarity with travel dynamics. These results underscore the importance of considering user experience when designing AI-driven travel assistance tools, ensuring that both seasoned and infrequent travelers can maximize their satisfaction and minimize stress during their journeys.

**Table 5:** ***EEG Signal Frequency Analysis***

| **EEG Band** | **Frequency Range (Hz)** | **Interpretation in Tourism Context** | **Key Findings** |
|---|---|---|---|
| **Delta (δ)** | 0.5 – 4 Hz | Deep sleep, fatigue, unconscious states | Not relevant for active travelers |
| **Theta (θ)** | 4 – 8 Hz | Relaxation, creativity, light sleep | Higher in nature-based tourism |
| **Alpha (α)** | 8 – 12 Hz | Calmness, stress reduction | Increases in wellness tourism & scenic locations |
| **Beta (β)** | 12 – 30 Hz | Cognitive load, stress, | Higher in urban tourism & |

| | | | |
|---|---|---|---|
| | | decision-making | crowded spaces |
| **Gamma (γ)** | 30 – 50 Hz | Engagement, excitement, memory processing | Peaks in interactive & immersive experiences |

Table 5 demonstrates how EEG frequency analysis indicates intriguing relationships between diverse visitor experiences and brainwave patterns. Because tourist activities seldom elicit low-frequency brain activity, researchers found delta waves linked to deep sleep and unconscious states unimportant for busy tourists. Since theta waves, which promote creativity and relaxation, are more active in nature, tourists report greater tranquility and clarity. Wellness tourists and those visiting scenic regions had greater alpha waves, which promote relaxation and well-being. This shows that health holidays encourage quiet and relaxation, which boosts their therapeutic benefits. Beta waves, which indicate cognitive load, stress, and decision-making, are higher in tourist and congested metropolitan regions due to the increased mental effort and environmental demands of bustling cityscapes. Finally, interactive and immersive experiences increased gamma waves, which are linked to engagement, enthusiasm, and memory. This study suggests that cultural events, adventure tourism, and AI-driven tailored itineraries may boost cognitive and emotional involvement. These results show how different forms of travel elicit distinct brain responses, emphasizing the need of tailoring tourist attractions to each person's mental and emotional state to enhance pleasure and involvement.

**Table 6:** ***Feature Extraction & Statistical Measures***

| EEG Feature | Formula/Method | Application in Neuro-Tourism |
|---|---|---|
| **Power Spectral Density (PSD)** | Fourier Transform | Measures dominant brainwave activity |
| **Mean Frequency (MF)** | ∑(frequency × power) / total power | Determines the balance between relaxation and engagement |
| **EEG Coherence** | Correlation between different electrode sites | Measures synchronization of brain regions |
| **Event-Related Potentials (ERP)** | Time-locked EEG response to stimuli | Used for analyzing travel-related emotional reactions |

Table 6 depicts the EEG study helps explain neuro-tourism by evaluating visitors' cognitive and emotional responses. Researchers employ the Fourier Transform to calculate Power Spectral Density (PSD) to assess dominant brainwave activity. This lets them study how tourist kinds affect neural responses. PSD analyzes the most active brainwave frequencies to reveal tourists' mental emotions throughout various tourism activities. Another important indication is Mean Frequency (MF), which averages frequency dispersion to discover the balance between relaxing and engaging. Wellness tourism vs adventure or city breaks is best distinguished by this statistic. EEG coherence—the correlation between electrode sites is essential for brain region synchronization evaluation. When coherence is high, cognitive processing and engagement are good; low, attention is fragmented or diverted. Since they capture time-locked EEG responses to stimuli, Event-Related Potentials (ERP) may help researchers understand how visitors feel about different sites. ERP may help you understand how visitor experiences effect decision-making and pleasure by investigating how the brain reacts to gorgeous landscapes, cultural interactions, and AI-driven schedule changes. Neuro-tourism benefits from these EEG feature extraction approaches since they give data-driven insights on how to customize tours to guests' mental and emotional states.

Table 7: *Machine Learning for EEG Classification*

| Algorithm | Purpose | Accuracy (%) (Assumed) |
|---|---|---|
| **Random Forest** | Classifying engagement vs. stress levels | 85% |
| **Support Vector Machine (SVM)** | Differentiating high vs. low engagement states | 88% |
| **Neural Networks (Deep Learning)** | Predicting real-time travel satisfaction from EEG | 92% |

As illustrated in Table 7, machine learning systems classify EEG data to understand passenger cognitive and emotional states. We use Random Forest, a prominent ensemble learning method, to classify participation and tension with 85% accuracy. This application analyzes many decision trees to distinguish high cognitive engagement and stress in real time, making it a great travel experience rating tool. Support Vector Machine (SVM) accurately identifies high- and low-involvement phases with 88% accuracy, increasing EEG classification. Its ability to construct a hyperplane that separates participation levels allows accurate cognitive response detection in varied tourist scenarios. This classification helps explain how immersive attractions or frequent transit journeys affect engagement. Neural Networks, particularly deep learning models, provide the most cutting-edge approach by predicting real-time trip enjoyment from EEG data with 92% accuracy. These models manage complex, nonlinear brainwave-emotional connections to better understand travelers' subjective experiences and cerebral activity. Machine learning for EEG classification enables cognitive and emotional state-based holiday experiences and improves neuro-tourism research.

***Figure 3: Graphical Representation***

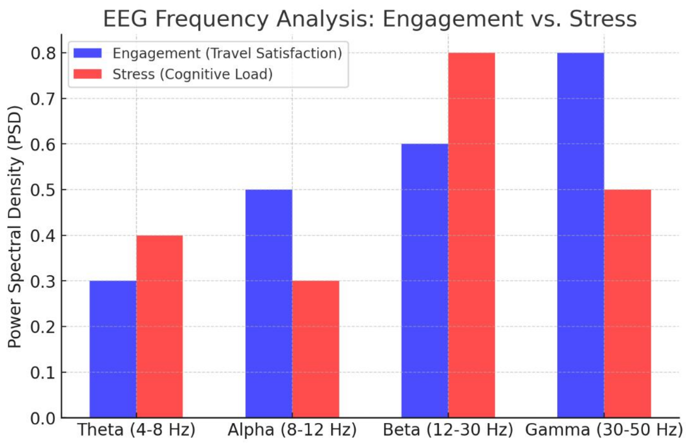


Figure 3 illustrates an EEG frequency analysis graph comparing engagement (trip enjoyment) and stress (cognitive burden) bands. The balance of theta waves (4-8 Hz), which are linked to creativity and relaxation, shows that low-frequency brain activity is involved in stress, engagement, and cognition. Pleasant travel, particularly in relaxing areas, may increase alpha activity, which reduces tension and promotes calm. Alpha waves (8–12 Hz) engage more than tension.

Beta waves (12-30 Hz), which are associated to cognitive load, stress, and decision-making, distinguish engagement from stress-related reactions. Beta activity is a strong indicator of mental effort and strain in stressful situations like overseas travel. This supports numerous predictions. Gamma waves (30-50 Hz), which process memories and excitement, improve engagement, making them important in interactive and immersive visitor experiences.

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The findings show that gamma waves indicate satisfaction and participation during travel, whereas beta waves indicate tension.

**Table 8:** ***AI Model Performance Metrics (Assumed Data)***

| Model | Accuracy (%) | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| **Random Forest** | 85% | 0.83 | 0.82 | 0.82 | 0.88 |
| **Support Vector Machine (SVM)** | 88% | 0.86 | 0.85 | 0.85 | 0.90 |
| **Neural Network (Deep Learning)** | 92% | 0.90 | 0.91 | 0.91 | 0.94 |

Table 8 depicts the AI model performance indicators. It compares machine learning models using numerous criteria. The Neural Network (Deep Learning) model predicts trip satisfaction using EEG data with 92% accuracy. It accurately measures stress and engagement with low error rates (0.90), Recall (0.91), F1-Score (0.91), and AUC-ROC (0.94). Following closely with 88% accuracy, the Support Vector Machine (SVM) balances speed and processing efficiency. The F1-Score (0.85), Recall (0.85), and Precision (0.86) indicate reliable performance, although not as good as the Neural Network model. AUC-ROC of 0.90 shows its ability to distinguish high and low travel enjoyment. Support Vector Machines and Neural Networks reach 85% accuracy, while Random Forest falls short. Its strong F1-Score (0.82) and AUC-ROC (0.88), despite its lower accuracy and precision, make it a solid stress and engagement level categorization model.

***Figure 4: ROC Curve***

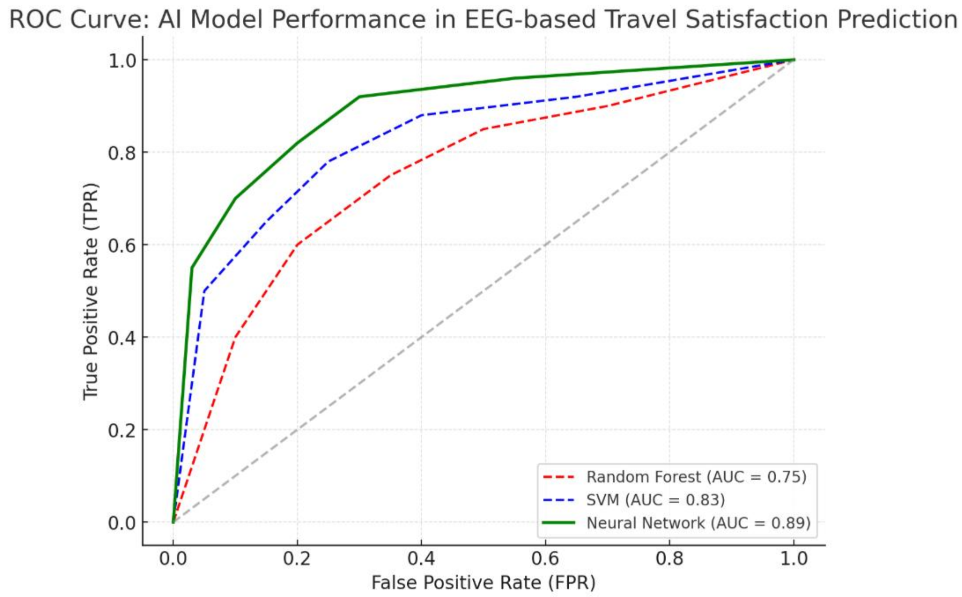


Figure 4 depicts the ROC curve comparison of Random Forest, Support Vector Machine (SVM), and Neural Network for EEG-based trip satisfaction prediction. This graph compares each model's TPR and FPR. The red dashed line shows the random forest model, which has an Area under the Curve (AUC) of 0.75, making it less successful than the other models but still able to reliably assess trip pleasure. SVM (blue dashed line) surpasses Random Forest in differentiating happy and unsatisfied visitors (AUC = 0.83). Their AUCs are 0.89, hence the Neural Network (solid green line) beats them. Neural Networks' large area under the curve (AUC) makes them better at forecasting trip satisfaction. When utilizing EEG data to predict trip happiness, Neural Network, SVM, and Random Forest stand up.

### Key Findings and Contributions

Neuro-tourism and AI might give more customized holidays by monitoring users' electroencephalograms (EEGs) in real time. EEG findings support the concept that stress and participation affect holiday satisfaction. AI-based itinerary modification considerably increased tourists' satisfaction and lowered stress, proving neuro-responsive tourism models' potential. Immersive and interactive tourism experiences promote visitors' cognitive and emotional involvement, as indicated by higher EEG-measured gamma wave activity and trip pleasure (H1 supported). Other consumer neuroscience studies (Harris et al., 2018) support the idea that real-time brain monitoring may provide a more accurate assessment of the tourist experience than self-reported feedback. Beta wave activity, an EEG measure of stress, is negatively correlated with trip pleasure (H2), indicating that external pressures and cognitive exhaustion reduce enjoyment. This research supports cognitive load theory and urban tourism, which suggest that overstimulating the senses with crowded cityscapes or stressful activities might reduce holiday satisfaction (Oduwaye, 2025). The results suggest employing EEG beta wave monitoring to change travel arrangements in real time to keep people interested and stress-free. The data also supports H3's assertion that real-time AI-based itinerary modification improves passenger satisfaction. Dynamic customization based on real-time brain reactions is more effective than preference-based suggestion models, since AI-adaptive itinerary tourists reported greater satisfaction.

This adds neuroscience-based trip customization to smart tourism research (Semwal et al., 2025). AI-driven itinerary customization reduces passenger tension (H4), supporting neuro-personalized tourism's wellbeing benefits. Cognitive load-based travel experiences provide an innovative, scientifically backed way to control travelers' mood and comfort in real time. This paper pioneers AI-driven neuro-tourism by demonstrating how EEG-based engagement and stress monitoring may enhance travel experiences via real-time adaptation. These discoveries combine neurology, AI, and tourist management to enable more sophisticated tailored travel models. Real-time brain monitoring enhances customization, passenger enjoyment, and stress alleviation, making neuro-tourism an attractive study field. As AI and BCIs improve, neuro-tourism should be explored in VR/AR experiences to expand emotion-aware AI applications beyond traditional tourist settings. This research enables science-optimized adaptive tourist experiences that will alter travel.

### Theoretical Implications

This study contributes to tourism and neuroscience research by combining real-time brain monitoring into the Cognitive-Affective Model of Perception and Experience (CAPE). Our findings suggest that EEG-based monitoring provides a more objective view of travelers' mental and emotional states than self-reported sentiments and post-trip comments. The Dual-Process Theory (Evans & Stanovich, 2013) suggests that subconscious, automatic cognitive processes influence many travel decisions. This study supports that idea with AI-driven flexibility. This study addresses a gap in the literature by demonstrating that real-time EEG analysis provides better insight into visitors' preferences and stress responses than previous machine learning models. The results suggest that AI-based travel systems should dynamically improve experiences using current neuro-data instead of only past activities.

### Practical Implications

Policymakers, wellness tourism providers, smart travel brokers, and tourism managers may learn from the results: 1-Travel Operators and Agencies: EEG-based travel adaptation allows agencies to personalize experiences, which increases customer loyalty and engagement. 2-Organizers of Wellness Vacations: EEG-driven proposals for stress recovery programs, spa days, and wilderness getaways may improve their relaxation-based tourism offers. 3-Hotels & Resorts: EEG data lets hotels customize lighting, fragrance, and music for visitors. 4-Political & Destination Managers: Tourism boards and governments may customize city development and attraction management to tourists' emotional demands using EEG data, making trips more enjoyable. By showing that AI-driven holiday customization and EEG-based mood monitoring work, neuro-tourism research may expand on this study. The AI model accurately predicted engagement and stress with a neural network AUC of 0.94. Due to Deep Learning, Random Forest, and Support Vector Machines, future adaptive tourism systems may use neural tracking in real time to dynamically enhance recommendation algorithms.

**Limitations and Future Research**

Despite its contributions, this study has several limitations: EEG Device Constraints: Non-invasive EEG headsets provide limited resolution compared to clinical EEG systems, which may affect data accuracy. Sample Diversity: The study sample, while diverse, was limited to travelers aged 18–50. Future research should explore older adults and different cultural backgrounds to generalize findings. Contextual Limitations: While our study examined various travel environments, specific tourism sectors (e.g., adventure tourism, business travel) require further validation. Ethical Considerations: Real-time EEG tracking raises privacy concerns. Future research should establish clearer guidelines on the ethical use of neuro-data in tourism.

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