

Generative artificial intelligence for sustainable tourism: alleviating cognitive overload to foster well-being and eco-responsible behavior

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ABSTRACT

The rise of AI-driven technologies, particularly generative AI (GenAI) like ChatGPT, is transforming customer service in hospitality and tourism sectors. These systems enhance user experiences by offering real-time, personalized support and 24/7 assistance. Yet, as sustainability becomes a key factor in travel decisions, consumers increasingly face information overload due to the abundance of eco-friendly options. This study examines how GenAI can alleviate this cognitive strain in sustainability-focused tourism contexts. Across two experiments (i.e., one on trip planning and another on on-site shopping), the findings show that more advanced GenAI tools significantly reduce information overload, improving decision-making and thus enhancing user perceptions of trust which in turn trust increases both well-being and behavioral intentions to use GenAI tools. On the other hand, the reduction of perceived decision risk increases behavioral intentions to use GenAI tools. In particular, by simplifying access to and comparison of eco-certified travel and shopping options, GenAI encourages more environmentally responsible consumer behavior.

1. Introduction

Artificial intelligence (AI) increasingly mediates consumer decision-making in e-commerce, finance, and tourism by automating data filtering, personalizing information, and enabling human-like interaction (Kaplan & Haenlein, 2019; Gursoy, Li, & Song, 2023). A major recent shift is generative AI (GenAI), which leverages large language models (LLMs) to produce contextually rich, adaptive responses. By providing real-time, personalized assistance (e.g., answering questions, recommending options, and facilitating transactions), GenAI reduces user effort, streamlines interactions, and helps consumers make more informed choices while limiting information fatigue and time spent comparing alternatives (Bang et al., 2023; Cao et al., 2021; Dwivedi et al., 2024).

Tourism offers especially strong potential for GenAI because travel planning requires many fragmented, information-intensive decisions (e.g., transportation, accommodation, destination research, and activity booking). Although platforms such as Tripadvisor and Booking.com

remain central to travel planning (Statista, 2024), their fragmented interfaces can intensify cognitive overload (The Verge, 2024). Tourists often face choice overload, inconsistent reviews, and uncertainty about cost, timing, and environmental impact. In contrast, GenAI, especially ChatGPT, can function as a super-aggregator, integrating search, comparison, and planning across services while filtering and structuring options in a single conversational flow (Tourism AI Network, 2024; Bang et al., 2023; Espejel et al., 2023; Zhang et al., 2024).

This advantage may be even more consequential for sustainability-oriented tourism, where decisions are inherently more cognitively demanding (Higham & Miller, 2018). Tourists must weigh carbon footprints, social responsibility certifications, ethical sourcing, and local community impacts alongside conventional criteria such as price and comfort (Scott & Gössling, 2022a, 2022b, 2022c; Zhang et al., 2024). These complex trade-offs can trigger decision fatigue, heighten cognitive strain, and weaken pro-environmental behavioral intent (Lindenberg & Steg, 2007; Scheibehenne et al., 2010). GenAI may mitigate these burdens by curating content, reducing perceived effort, and supporting

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more confident, eco-friendly choices (Hu & Krishen, 2019; Sweller, 2010).

The growing market for GenAI-based chatbots underscores this momentum, with projections rising from \$2.47 billion in 2021 to \$24.64 billion by 2030. ChatGPT, launched in 2022, rapidly reached 100 million users within two months and reportedly averages 100 million daily visitors (Niu & Mvondo, 2024). Using advanced natural language processing and machine learning, it generates tailored responses from large-scale text data, positioning it as a powerful tool for customer engagement and service transformation (Kim, Kim, Park, et al., 2023; Szatvanyi, 2023).

However, much of the earlier chatbot adoption literature relies on TAM and UTAUT, emphasizing perceived usefulness and ease of use (Balakrishnan et al., 2022; Davis, 1989; Rese et al., 2020; Venkatesh, Morris, Davis, & Davis, 2003). In sustainability-focused tourism, these frameworks may be insufficient because ease is not only about interface simplicity but also about managing complex, value-laden information. When users must evaluate conflicting sustainability criteria, cognitive effort rises substantially, increasing the risk of information overload and reduced confidence (Eppler & Mengis, 2004; Sweller, 1988). This dynamic can contribute to the well-documented gap between sustainability awareness and actual behavior.

GenAI offers a plausible route to reduce this paradox by lowering mental effort and enabling decisions more aligned with pro-environmental values. Yet, whether GenAI consistently alleviates cognitive strain and fosters sustainable behavior remains unclear. Given that sustainable tourism targets long-term environmental, social, and economic well-being (World Tourism Organization, 2022), clarifying GenAI's role in sustainable choice-making is theoretically and practically important.

Accordingly, this study examines the cognitive and behavioral implications of GenAI in tourism planning under sustainability complexity. Drawing on Information Processing and Cognitive Load Theory (Sweller, 1988) and transformative marketing perspectives (Sirgy, 2012), it focuses on information overload, perceived risk, trust, well-being, and behavioral intentions. The central premise is that GenAI's capacity to filter, summarize, and structure information may moderate the cognitive costs of sustainability evaluations and shape adoption intentions in high-density decision environments.

The research addresses four questions: (1) How do sustainability-related searches influence perceived cognitive overload, trust, risk, and well-being in complex tourism decisions? (2) To what extent do differences in GenAI capability (e.g., GPT-4 vs. GPT-3.5) moderate the cognitive impact of sustainability considerations during pre-trip and on-site decisions? (3) How does advanced GenAI reduce decision fatigue and enhance trust, well-being, and perceived risk reduction in sustainability-related travel scenarios? (4) What role does GenAI-driven information structuring play in shaping intentions to adopt AI tools in sustainability-focused tourism contexts?

Two experiments test these propositions. Study 1 examines pre-trip planning with 500 U.S. participants using either GPT-3.5 or GPT-4 to plan a trip to China, evaluating sustainable and non-sustainable options. Study 2 assesses on-site behavior during sustainable versus non-sustainable shopping searches. Both employ a 2 × 2 between-subjects design and measure information overload, trust, risk perception, well-being, and behavioral intentions. ANOVA and moderated mediation analyses reveal that sustainability-oriented searches increase perceived information overload, but GPT-4, unlike GPT-3.5, mitigates these effects through superior filtering and structuring. Reduced cognitive load is associated with higher trust, greater well-being, and lower perceived risk, highlighting the value of advanced GenAI for decision-making under sustainability-driven complexity.

The findings refine theory by showing that GenAI can reduce overload in sustainability-related tourism searches and broaden "ease of use" in adoption research. Beyond interface simplicity, ease increasingly involves clarity, informational purification, and structural coherence in

cognitively and emotionally taxing over-choice contexts (Iyengar & Lepper, 2000). By showing that GenAI summarization and personalization can enhance trust and well-being while lowering perceived risk (Hu & Krishen, 2019; Meyer-Waarden & Cloarec, 2022), the study extends TAM and UTAUT and contributes to work on technology trust, transformative marketing, and risk perception (McKnight et al., 2011; Roca et al., 2009; Sirgy, 2012). It also reflects the shift from rule-based chatbots to LLM-driven, goal-sensitive systems (Dwivedi et al., 2024; Kaplan & Haenlein, 2019), positioning GenAI as a tool for reducing cognitive overload and supporting sustainable tourism decisions.

2. Literature review and theoretical foundations

Key empirical studies (Table 1) on chatbot and GenAI adoption across choice contexts highlight how the field has evolved from first-generation, task-oriented chatbots in retail and e-commerce toward LLM-based systems, especially ChatGPT, in tourism and broader decision environments. It organizes prior work by theoretical grounding (dominantly TAM/UTAUT and extensions, alongside uncertainty reduction, affordance-based, expectation confirmation, and choice overload perspectives), focal variables (e.g., perceived usefulness/effort, information accuracy, anthropomorphism, trust, privacy, option structuring, and recommendation satisfaction), methods, and core findings. Across studies, functional value and hedonic benefits generally increase acceptance, while privacy concerns and incorrect information undermine trust and downstream intentions; more recent tourism research additionally shows that the way GenAI structures or reduces options can either relieve or exacerbate cognitive strain. By juxtaposing these results, the table clarifies converging evidence on trust and information quality as central mechanisms, while revealing a remaining gap regarding how advanced GenAI capabilities shape cognitive overload, perceived risk, and well-being in sustainability-intensive tourism decisions, directly motivating the present research.

2.1. Evolution of conversational agents: from rule-based scripts to LLMs

Early chatbots relied on rule-based logic and keyword matching, which restricted flexibility and often produced unsatisfying interactions. The rise of transformer-based models and LLMs has shifted conversational AI toward contextual understanding, dynamic language generation, and scalable personalization (Dwivedi et al., 2024; Kaplan & Haenlein, 2019). This transition is visible in tourism, where GenAI can consolidate fragmented planning tasks (e.g., transport, accommodation, activities) into a single conversational journey, effectively moving users from interface-driven search to goal-driven assistance (Bang et al., 2023; Espejel et al., 2023). Compared with earlier systems, LLM-based tools are increasingly valued not just for automation but for their capacity to structure complex information and simulate knowledgeable, responsive support. This paradigm shift lays the groundwork for explaining why adoption logics may now extend beyond traditional usability to include trust, accuracy, and cognitive relief.

2.2. Adoption fundamentals: TAM/UTAUT streams and core drivers

Most empirical evidence on conversational AI adoption is grounded in TAM and UTAUT extensions, emphasizing functional and experiential value. In retail and service contexts, perceived usefulness, ease of use, and enjoyment are consistent predictors of acceptance, while privacy concerns inhibit adoption (Balakrishnan et al., 2022; Rese et al., 2020). Studies also show that information quality enhances trust and behavioral intention: accuracy improves trust in AI and strengthens acceptance across cultures (Kim et al., 2021), and usability and responsiveness increase satisfaction in e-commerce settings (Chen et al., 2021). Beyond functionality, perceived intelligence and anthropomorphism can shape attitudes and intentions (Balakrishnan et al., 2022). These findings establish a robust baseline: users adopt conversational AI when it is

Table 1
Literature review about chatbots and GenAI.

Authors	Background	Type of AI/Sector/ Variables	Method	Findings
Rese et al. (2020)	TAM Uses and gratification theory	Chatbots in retail choice situations Perceived usefulness Ease of use Enjoyment Behavioral intention to use	Survey (n = 205) Germany	Perceived usefulness and enjoyment positively influence chatbot acceptance Privacy concerns negatively influence acceptance
Kim et al. (2021)	TAM Information system model	Chatbots in retail choice situations Accuracy of information Trust in AI Behavioral intention to use	Scenario-based survey (n = 793) Korea/New Zealand	Information accuracy increases trust and behavioral intentions Trust positively affects user acceptance
Chen et al. (2021)	TAM Information system success model	Chatbots in e-commerce choice situations Usability Extrinsic values Responsiveness Intrinsic values Satisfaction	Survey (n = 425) USA Asia Europe	Usability positively impacts user experience Extrinsic/intrinsic values enhance satisfaction Usability and responsiveness lead to satisfaction
Balakrishnan et al. (2022)	UTAUT	Chatbots in retail/service choice situations Performance expectancy Effort expectancy Facilitating conditions Social influence Perceived intelligence Anthropomorphism Attitudes Behavioral intention to use	3 scenario-based surveys (n = 420) India	Performance-/effort expectancy, facilitating conditions, social influence, perceived intelligence, and anthropomorphism positively influence attitudes towards chatbots and intention to use
Zhu et al. (2022)	Lay theories Uncertainty reduction theory	GenAI in technology choice Certainty consumer needs Perceived effectiveness Perceived empathy Type of GenAI User acceptance	3 scenario-based surveys (n = 156, 268, 260)	Preference Gen AI chatbots with clear role definitions Need for security increases perceived effectiveness, promoting acceptance Perceived effectiveness mediates impact of certainty on acceptance
Ali et al. (2023)	Affordance actualization theory	ChatGPT in Tourism industry Relevance Credibility Usefulness Intelligence Trust Behavioral intention to use	2 scenario-based surveys (n = 102, 344) India	Relevance, credibility, usefulness, intelligence of personalized recommendations enhance trust, which positively influences behavioral intentions
Hsu and Lin (2023)	Expectation confirmation model	Chatbots in retail/service choice situations Efficiency Privacy Responsiveness Perceived contingency Satisfaction Loyalty	Scenario-based survey (n = 219) Taiwan	Service quality and satisfaction positively influence user loyalty Responsiveness improves satisfaction with AI chatbot services and boosts loyalty
Kim, Kim, Kim, and Park (2023)	Theory of choice overload and decision-making	ChatGPT in tourism industry Number of options Recommendations Perceived accuracy Recommendation satisfaction Behavioral intention to use	Scenario-based surveys (5 studies: n = 265, 315, 440, 210, 251) USA	Accuracy positively impacts recommendation satisfaction Increased choices increase satisfaction with ChatGPT. In situations of choice overload some users find ChatGPT more favorable due to the abundance of options, others experience feelings of overwhelm and cognitive strain.
Kim et al. (2023)	UTAUT2	ChatGPT in tourism industry Information correctness User reliance Visit intentions for recommended destinations Perceived accuracy & trustworthiness Type and prominence of incorrect information	Surveys (n = 153, n = 222, n = 214, n = 298, n = 335, n = 325) USA UK	Incorrect information reduces recommendation acceptance and visit intentions Trust moderates the negative impact of incorrect information
Shin et al. (2023)	UTAUT2 TAM	ChatGPT vs humans in tourism industry Perceived trustworthiness Option reduction Recommendation	Multiple experimental studies (Study 1A: n = 333, Study 1B: n = 326, Study 2: n = 315, Study 3: n = 130, Study 4: n = 258) USA	Excessive option reduction lowers decision satisfaction due to perceived loss of choice Trust in AI and human autonomy are key factors, with a hybrid decision-making approach improving outcomes

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Table 1 (continued)

Authors	Background	Type of AI/Sector/ Variables	Method	Findings
Xiong et al. (2024)	UTAUT2 AGS Method	satisfaction Visit intention Size of initial options Agents of option reduction and initial recommendation ChatGPT in tourism industry Tourist expectations Destination social responsibility (DSR) and motivation Data consistency Cost-effectiveness Willingness to interact Travel & purchase intentions	Multiple studies (Study 1A: n = 146, Study 1B: n = 143, Study 1C: n = 312, Study 2: Experimental) USA	Improvement destination research by simulating diverse perspectives. Enhanced data consistency and cost-effectiveness, reducing human variability, increase travel and purchase intentions.
Niu and Mvondo (2024)	ISS TAM Affinity theory Coolness theory Posthumanism	ChatGPT in different choice situations Perceived usefulness Technology affinity Information quality Perceived coolness Satisfaction Ethical beliefs User loyalty	Exploratory qualitative study (n = 41) USA	Perceived coolness, satisfaction, reliability, and quickness boost usefulness and satisfaction User satisfaction is influenced by technology affinity, coolness, and posthuman ability, which increase loyalty Ethical beliefs negatively moderate satisfaction and loyalty
Abadie et al. (2024)	UTAUT TAM	ChatGPT in different choice situations Performance Expectancy Excellence Status esteem Aesthetics Ethics Behavioral intention to use	Survey (n = 195) UK	Performance expectancy, excellence, meaningfulness of recommendations enhance behavioral intentions to use Conversational abilities positively impact user engagement
Majid et al. (2025)	UTAUT2 TAM AIDUA PEB Spillover theory	Chatbots vs humans in tourism industry Performance-/effort expectancy Personalization Credibility Efficiency Demographics	Exploratory qualitative study (20 interviews, 12 focus groups) Indonesia	Hybrid decision-making combining chatbots and humans optimizes satisfaction in pre-trip planning Enhanced tourism experiences and promoted sustainable behavior, especially in nature-based destinations

useful, effortless, enjoyable, and trustworthy. Yet these models largely emerged from first-generation systems, leaving open how GenAI's expanded capabilities reshape the meaning of ease, quality, and value in complex decisions.

2.3. Trust, accuracy, and recommendation architecture in tourism GenAI

Recent tourism research shifts attention from general acceptance to the mechanics of AI-supported choice. In ChatGPT-assisted travel decisions, perceived accuracy and trustworthiness are central: incorrect information reduces recommendation acceptance and visit intentions, with trust buffering these effects (Kim, Kim, Park, et al., 2023). The structure of recommendations also matters. Excessive option reduction can lower satisfaction due to perceived loss of choice, suggesting that optimal outcomes may require a balance between AI guidance and user autonomy (Shin et al., 2023). Personalized and credible recommendations further enhance trust, which in turn increases behavioral intentions (Ali et al., 2023). These studies indicate that GenAI's value in tourism is not only what it recommends but how it curates, frames, and justifies choices. This builds toward a more balanced view of adoption in which trust and recommendation design mediate the path from AI capability to intention.

2.4. Cognitive overload and sustainability complexity: toward an integrated lens

A smaller but growing stream addresses cognitive burden and choice overload, issues especially salient for sustainability-oriented tourism. Choice overload research suggests that users may appreciate abundant options from ChatGPT, yet still experience overwhelm, implying heterogeneous cognitive thresholds (Kim, Kim, Park, et al., 2023). Beyond tourism, consumers prefer GenAI with clearly defined roles, and perceived effectiveness can mediate needs for certainty and security (Zhu et al., 2022). Qualitative evidence also supports hybrid decision-making, where chatbots and humans jointly optimize satisfaction and can even encourage sustainable behavior in nature-based contexts (Majid et al., 2025). These insights align with Cognitive Load Theory, which predicts that limited processing capacity makes complex, multi-criteria evaluations prone to strain (Sweller, 1988, 2010). Integrating this perspective with trust and well-being frameworks (McKnight et al., 2011; Roca et al., 2009; Sirgy, 2012) highlights a key gap: we still lack clear evidence on how advanced GenAI capabilities reduce overload and perceived risk specifically when sustainability trade-offs intensify decision difficulty.

3. Conceptual model and hypotheses

3.1. Sustainable information search characteristics

Sustainability has become a central expectation in tourism, yet it introduces a distinctive cognitive burden: choosing "greener" options requires processing more criteria, less familiar information, and harder trade-offs than conventional travel planning. Compared with standard itinerary building, sustainability-oriented searches add layers such as eco-certifications, carbon impacts, local sourcing, labor and community considerations, and waste or resource practices, attributes that are often inconsistent across providers and difficult to verify. As information volume and attribute conflict rise, users face classic choice- and information-overload dynamics, including greater cognitive strain and decision fatigue (Eppler & Mengis, 2004; Gourville & Soman, 2005a, 2005b; Iyengar & Lepper, 2000; Scheibehenne et al., 2010).

This challenge is amplified by the broader data environment. Real-time sustainability metrics and proliferating "green" signals (e.g., footprint estimates, environmental indicators, label schemes) can enrich decisions but also expand the informational field users must interpret and prioritize (Li & Huang, 2023). In sustainability-focused tourism,

decisions also carry moral weight, further increasing cognitive demands because users are not only optimizing for personal utility but also negotiating ethical considerations (Lindenberg & Steg, 2007; Schwartz, 1994). Overall, sustainability is not merely an added feature of travel planning, it fundamentally increases decision complexity, making overload more likely (Bettman et al., 1998).

H1. Searching for complex sustainability-related travel experiences increases information overload.

3.2. AI capability

AI capability can be understood as a system's capacity to interpret inputs, learn from data, and flexibly adapt its outputs to accomplish goals (Kaplan & Haenlein, 2019). In conversational settings, this capability matters because user requests are typically unstructured and context-dependent; more advanced models are better able to infer intent, maintain context, and translate vague queries into actionable guidance (Duan et al., 2019; LeCun et al., 2015; Radford, 2018).

In sustainability-focused travel planning, the core challenge is not information scarcity but informational complexity: many attributes, inconsistent signals, and difficult trade-offs. Conceptually, high-capability GenAI can function as a cognitive scaffold by curating, filtering, and summarizing sustainability content into decision-relevant chunks, reducing extraneous cognitive load and limiting the escalation from "more criteria" to "more overload" (Eppler & Mengis, 2004; Sweller, 1988, 2010). Prior work shows that when information is structured and tailored, rather than merely abundant, users process it more efficiently and experience less decision fatigue (Hu & Krishen, 2019). Because higher-capability systems (e.g., GPT-4 vs. GPT-3.5) generally offer stronger contextual understanding, response quality, and personalization, they should be especially effective at dampening overload in complex sustainability searches (Espejel et al., 2023; Dwivedi et al., 2024).

H2. AI capability negatively moderates the positive effect of searching for complex sustainability-related travel experiences on information overload.

3.3. The transformative trust-risk framework

3.3.1. Well-being

Well-being has become a central outcome in transformative marketing and technology research because technologies shape not only what people choose, but also how they feel while choosing (Diener, 1984; Sirgy, 2012; Diener & Chan, 2011). Conceptually, well-being reflects the extent to which individuals evaluate experiences positively, combining cognitive appraisals (e.g., "this feels manageable") and affective states (e.g., stress vs. comfort) (Rozanski & Kubzansky, 2005). In complex decision environments, this evaluative experience is tightly linked to the demands placed on limited cognitive resources (Higgins, 1997; Avnet & Higgins, 2006).

Information overload is therefore expected to harm well-being because it taxes attention, increases perceived effort, and fosters decision fatigue. When users must process excessive, conflicting, or hard-to-verify information, typical in sustainability-oriented travel planning, cognitive strain spills into negative affect, lowering satisfaction and psychological comfort (Eppler & Mengis, 2004; Gourville & Soman, 2005a, 2005b; Iyengar & Lepper, 2000). As cognitive resources become depleted, people experience more stress and less perceived control, which undermines well-being (Schroder, Driver, & Streufert, 1967; Lindenberg & Steg, 2007).

H3a. Information overload when searching for complex sustainability-related travel experiences reduces user well-being.

Well-being also serves as a motivational pathway into continued technology use. Behavioral intention—one's willingness to engage with

a technology—strengthens when the experience delivers psychological benefits such as reduced stress, greater clarity, and a sense of cognitive comfort (Venkatesh et al., 2012; Meyer-Waarden et al., 2020). In sustainability-focused decisions, tools that simplify complexity and make trade-offs easier to navigate are valued not only for efficiency but for how they change the decision experience, turning a taxing process into a manageable one (Eppler & Mengis, 2004; Sweller, 1988). As GenAI-based support can enhance comfort and reduce strain, improvements in well-being should translate into stronger intentions to keep using the technology (Davis & Pechmann, 2013; Kim et al., 2020).

H3b. Well-being increases users' behavioral intention to use GenAI when searching for complex sustainability-related travel experiences.

3.3.2. Technology trust

Technology trust reflects the expectation that a system is reliable, credible, and capable of performing as intended, especially under uncertainty (Lee & See, 2004; McKnight & Chervany, 2001). In AI-mediated decisions, trust is pivotal because users cannot fully observe how outputs are produced; instead, they rely on perceived competence, transparency, and controllability to judge whether the tool is safe to follow (Pavlou, 2003; Wu et al., 2011; Sarkar et al., 2020). In sustainability-oriented travel planning, this reliance is intensified: users face complex trade-offs, ambiguous “green” claims, and higher perceived consequences of choosing poorly.

Information overload is a direct threat to trust because it undermines perceived control and decision confidence. When people feel overwhelmed by excessive or conflicting information, they become less certain about their judgments and more skeptical of the aids guiding them, reducing trust in both the decision process and the technology supporting it (Dietvorst et al., 2015; Gefen et al., 2003; Gourville & Soman, 2005a, 2005b; Scheibehenne et al., 2010; Zhang et al., 2024). In this sense, overload does not merely burden cognition; it destabilizes the psychological foundation needed to rely on AI.

H4a. Information overload when searching for complex sustainability-related travel experiences reduces technology trust.

Trust is also consequential beyond adoption logic because it functions as a psychological safety cue. When users trust an AI system, the decision environment feels more predictable and less threatening, which lowers stress and supports a more comfortable decision experience, an effect emphasized in service and transformative marketing research (Ostrom et al., 2021; Meyer-Waarden & Cloarec, 2022; Cloarec, Cadieu, & Alrabie, 2024). This is especially relevant in sustainability decisions, where uncertainty and moral stakes can heighten cognitive and emotional load.

H4b. Technology trust increases user well-being when searching for complex sustainability-related travel experiences.

Finally, trust remains a central pathway into continued use. Believing that GenAI is dependable and credible strengthens willingness to rely on its recommendations, particularly when tasks are complex and personal expertise is limited (Lee & See, 2004; McKnight & Chervany, 2001). Accordingly, greater trust should translate into stronger intentions to use GenAI as a decision-support tool in eco-conscious travel planning (Gefen et al., 2003; Dietvorst et al., 2015).

H4c. Technology trust increases users' behavioral intentions when searching for complex sustainability-related travel experiences.

3.3.3. Perceived risk

Perceived risk captures users' anticipation of negative consequences when relying on a technology under uncertainty (Featherman & Pavlou, 2003). In GenAI settings, this extends beyond general performance concerns to include reliability (errors or misleading outputs), loss of control, privacy and security threats, and ethical unease, risks that can be functional, psychological, or, in some contexts, even physical (Roca

et al., 2009; Klobas et al., 2019; Penmetsa et al., 2019). These concerns become particularly salient in sustainability-oriented travel planning, where information is complex, verification is difficult, and the perceived stakes of “getting it wrong” are higher.

Information overload is expected to intensify perceived risk because it magnifies uncertainty and reduces users' perceived ability to evaluate or monitor the system's outputs. When people feel overwhelmed by excessive or conflicting information, they become more sensitive to the possibility of error, manipulation, or failure, especially in complex, high-involvement choices (Slovic, 1987; Scheibehenne et al., 2010; Gourville & Soman, 2005a, 2005b). In such conditions, GenAI may be seen as harder to control and easier to misjudge, elevating risk perceptions.

H5a. Information overload when searching for complex sustainability-related travel experiences increases perceived risk.

Risk is also theorized to carry emotional costs. Concerns about reliability, bias, privacy breaches, or ethical misalignment can trigger anxiety and reduce psychological comfort, particularly when decisions feel consequential and morally charged (Dogruel et al., 2015; Hohenberger et al., 2016; Subero-Navarro et al., 2022). Within transformative and service research, these threat appraisals are expected to erode well-being by making the decision experience feel tense rather than supportive (Ostrom et al., 2021; Meyer-Waarden et al., 2020; Meyer-Waarden & Cloarec, 2022).

H5b. Perceived risk when searching for complex sustainability-related travel experiences decreases user well-being.

Finally, perceived risk is a well-established inhibitor of technology acceptance: when users anticipate negative outcomes or feel unable to safeguard themselves, they avoid reliance and disengage (Asgari & Jin, 2019; Klobas et al., 2019). In GenAI-mediated sustainability decisions, elevated risk should therefore translate into weaker intentions to use the tool for future eco-conscious travel planning.

H5c. Perceived technology risk decreases users' behavioral intentions to use GenAI when searching for complex sustainability-related travel experiences.

3.4. Moderated mediation and controls

Sustainability-oriented travel search often creates a cascading burden: expanding choice sets and moral/eco criteria increases information volume and attribute conflict, which can trigger decision fatigue, undermine confidence, and weaken willingness to rely on decision aids (Gourville & Soman, 2005a, 2005b; Scheibehenne et al., 2010). In this setting, information overload functions as a key transmission mechanism through which sustainability-related complexity can spill over into poorer user experiences and weaker intentions to use GenAI-supported planning tools (Venkatesh et al., 2012; Meyer-Waarden et al., 2020).

GenAI capability should shape this cascade. High-capability systems can act as cognitive scaffolds: they translate sprawling “green” information into structured, prioritized, and personalized guidance, reducing extraneous load and limiting the extent to which sustainability search complexity turns into felt overload (Espejel et al., 2023; Hu & Krishen, 2019; Sweller, 1988). Conceptually, this means capability does not only change the direct experience of searching; it also alters the downstream pathway from sustainability complexity → overload → weakened adoption propensity. When overload is contained through better filtering and organization, the negative carryover into technology-use intentions should be reduced (Lee & See, 2004; Dwivedi et al., 2024).

H6. Higher GenAI capability decreases the negative indirect effect of complex sustainability-travel searches on GenAI-use intentions via information overload.

To account for systematic differences in how people navigate sustainability information and adopt GenAI, the model includes gender,

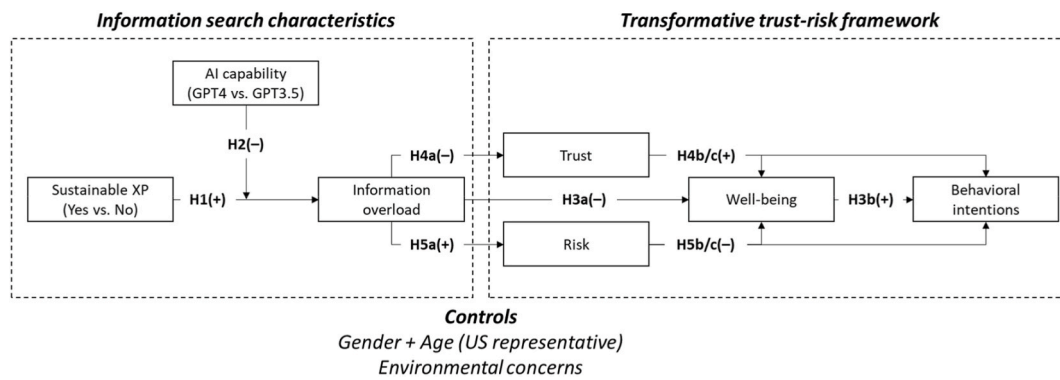


Fig. 1. Research model.

age, and environmental concern as controls. These factors can shape baseline cognitive processing, risk sensitivity, and openness to technology and pro-environmental guidance, helping isolate the theoretical effects of the focal mechanisms (Gefen & Straub, 1997; Bord & O'Connor, 1997). Environmental concern, in particular, captures the degree to which individuals are motivated by ecological issues, which can influence attention to sustainability cues and engagement with sustainability-oriented travel content, and, by extension, interaction patterns with GenAI tools in this domain (Dolnicar, 2020; Van der Werff, Steg, & Keizer, 2014a, 2014b).

Fig. 1 summarizes the conceptual model: sustainability-oriented travel search increases informational complexity, which can escalate cognitive load and ripple into downstream psychological and behavioral responses. GenAI capability is positioned as a buffering resource—an adaptive structuring mechanism that curates and simplifies sustainability content, making sustainable decision-making feel more manageable and thereby supporting engagement with AI-assisted planning.

4. Experimentations

The authors designed two experimental studies to explore the influence of sustainability considerations and AI capabilities on perceptions in tourism-related contexts. Using two different settings in tourism research—preparing for a trip (before the on-site experience) and shopping (during the on-site experience)—provides valuable insights into how AI capabilities and sustainability considerations influence perceptions at different stages of the travel journey. Examining these distinct phases enables a deeper understanding of how travelers interact with AI tools during trip planning and how such interactions evolve throughout on-site activities. This approach captured the dynamic nature of perceptions in tourism, offering a more comprehensive view of the impact of AI and sustainability on traveler experiences and behaviors throughout their journey.

Study 1 and Study 2 were designed to explore how sustainability-related decisions are influenced by AI capabilities across distinct decision-making contexts: pre-trip planning and on-trip activities. These two contexts represent different cognitive and emotional demands, thereby offering a holistic understanding of the impact of AI tools and sustainability considerations in tourism-related scenarios. Study 1 focused on the preparation phase of travel, where participants planned a trip to China by searching for sustainable versus non-sustainable travel options using different AI tools. This phase involves long-term planning and requires extensive information gathering, typically associated with higher cognitive effort (Eppler & Mengis, 2004; Sweller, 1988) due to the complexity of pre-trip planning, where sustainability considerations added layers of information to process (Scheibehenne et al., 2010; Sweller, 2010). Conversely, in Study 2, the immediacy of on-trip shopping decisions highlighting the importance of AI tools in facilitating

quick, informed choices without overwhelming users. In contrast to Study 1, it examined the on-trip experience, specifically sustainable shopping decisions during a trip. This phase represents more immediate and action-oriented decision-making, which is influenced by situational factors and time constraints (Bettman et al., 1998).

The differences between study 1 and 2 investigate if AI capability plays a distinct role depending on the decision-making stage. The rationale for selecting two distinct stages lies in their unique demands on cognitive processing and user behavior. The pre-trip stage is characterized by extensive deliberation and forward-looking decisions, where users engage in detailed evaluations of multiple attributes, such as transportation modes, accommodations, and itineraries (Iyengar & Lepper, 2000). In contrast, the on-trip stage involves real-time decisions that are more situational and immediate, such as selecting sustainable shopping options during pre-trip planning, AI tools help manage detailed information, while during on-trip activities, they support efficient and stress-free decision-making in real-time (Zhang et al., 2024). By comparing these two contexts, this investigation aimed to identify whether the effects of AI capability and sustainability considerations differ depending on the nature of the decision-making stage. By examining both stages, this research provides a comprehensive view of how AI tools influence sustainability-focused decisions across varying cognitive demands, offering valuable insights into the broader applicability of GenAI technologies in tourism contexts. The objective was to determine whether AI tools' capacity to reduce information overload and enhance user well-being, trust, and behavioral intentions functions consistently across varying travel contexts.

To manipulate the level of AI capability, GPT-4 was used for high capability and GPT-3.5 for low capability. According to Wang et al. (2025), GPT-4 significantly outperforms GPT-3.5 in accuracy, reasoning, and problem-solving, achieving higher reliability with fewer errors. Its superior performance in comprehension and decision-making makes ChatGPT-4 particularly well-suited for industries that require precision and analytical thinking, such as the medical and education sectors. In scenarios involving chatbots that assist in decision-making, this can significantly affect the outcomes. GPT-4's ability to filter, analyze, and generate concise, accurate insights can help users efficiently navigate complex data, thereby reducing errors and decision fatigue. Furthermore, Farhat et al. (2024) demonstrated that GPT-4 showed greater accuracy and problem-solving ability compared to GPT-3.5, making it more reliable for complex reasoning and decision-making tasks. It outperformed other models across multiple subjects, reinforcing its suitability for business strategy, investment analysis, and AI-driven automation.

4.1. Study 1 – pre-trip planning to organize the journey

4.1.1. Research design

The authors conducted a 2x2 between-subject experiment to

investigate the impact of sustainable trip searches and AI capabilities on respondents' perceptions when preparing for a trip to China. The experiment was designed with two independent variables: the type of experience (sustainable vs. non-sustainable) and the AI model used (GPT-4 for high AI capability vs. GPT-3.5 for low AI capability). Participants were randomly assigned to one of four scenarios, where they were asked to seek out a sustainable trip with the assistance of either GPT-4 or GPT-3.5. The aim was to assess how the emphasis on sustainability, combined with the AI's capability, influences participants' perceptions.

4.1.2. Sample

The authors conducted an online survey using Qualtrics as the panel provider, with a total of 500 U.S. representative participants (Appendix 1). The mean age of respondents was 45.6 years, with a standard deviation of 17.4 years. The sample consisted of 53.6% women.

4.1.3. Measures

The authors used established scales measured on 7-point Likert scales to assess various constructs in this study (Appendix 2). Information overload was measured using a scale adapted from Hunter et al. (2024), which included items such as "ChatGPT enables me to process large amounts of information." The measurement scale for information overload was reversed to ensure that the relationships with other constructs reflect increased rather than reduced information overload, aligning with the intended interpretive direction. Well-being was assessed with a scale from Meyer-Waarden and Cloarec (2022), including items like "ChatGPT would improve my overall quality of life." Technology trust was measured using a scale from McKnight et al. (1998), with items such as "I would trust that ChatGPT is safe." Perceived risk was evaluated using a scale based on Lijarcio et al. (2019) and Yang et al. (2018), with items like "I am apprehensive about using ChatGPT." Behavioral intention to use was assessed using a scale from Venkatesh et al. (2012), which included the item "In view of its advantages, I intend to use ChatGPT for various tasks in the future." Lastly, environmental

concerns were measured using a scale from Schroder, Driver, and Streufert (1967), with items such as "I am concerned about the environment."

4.1.4. Data quality

The measurement model achieved a good fit, as indicated by the results of the confirmatory factor analysis. The chi-square value was 1104.613 with 335 degrees of freedom. The root mean square error of approximation (RMSEA) was .068, which is below the commonly accepted threshold of .08. The comparative fit index (CFI) was .937, and the Tucker-Lewis index (TLI) was .929, both of which exceed the usual threshold of .90.

All constructs demonstrated strong psychometric properties, achieving reliability with Cronbach's alpha values greater than .70 (Appendix 2). Convergent validity was established, as the average variance extracted (AVE) for each construct exceeded .50 (Appendix 2). Discriminant validity was confirmed, with squared correlations between constructs being lower than their respective AVE values (Appendix 3).

The authors confirmed that common method variance was not an issue (Podsakoff et al., 2003). Using the ConMET package (De Schutter, 2021), competitive models where items from two constructs loaded on the same latent variable were tested, all of which significantly worsened the fit of the measurement model (χ^2 significantly increased, $p < .001$; Appendix 4). Additionally, Harman's one-factor test (Harman, 1967) performed poorly compared to the measurement model ($p < .001$).

A post hoc power analysis using the semPower package (Jobst et al., 2021) indicated sufficient sample size for robust estimates. With an RMSEA of .068, a sample size of 500, 335 degrees of freedom, and an alpha of .05, the power was highly satisfactory ($b > .99$).

4.1.5. Results

4.1.5.1. ANOVA. The authors conducted an ANOVA to evaluate the effects of sustainable trip searches and AI capability on information overload (Fig. 2). The analysis revealed a significant main effect of

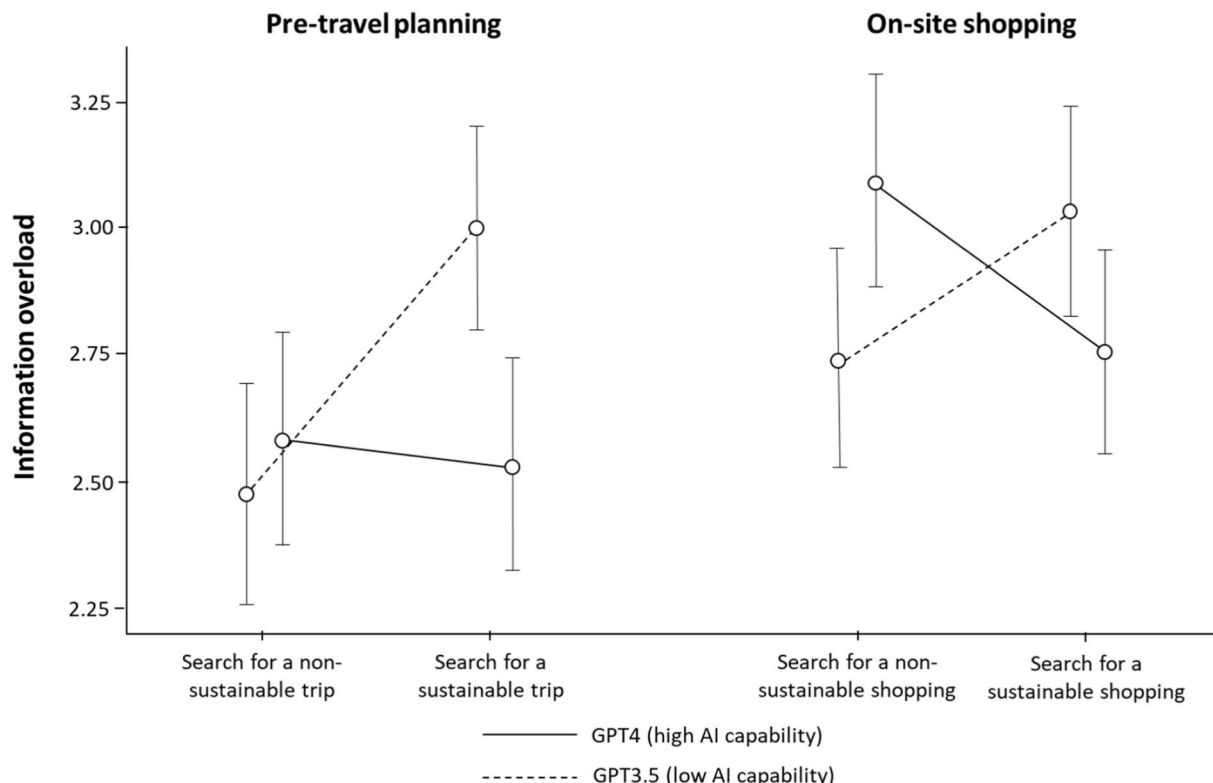


Fig. 2. Interactive effects of sustainable and non-sustainable trip and shopping searches and AI capability on information overload.

Table 2
Results for the moderated mediation analysis (Study 1).

Mediators	AI capability	Effect	95% CI		Index
			Lower	Upper	
INFO → T	Low	-.10*	-.1824	-.0258	.12 (95% CI =
	High	.02 ^{ns}	-.0401	.0806	[.0243, .2261])
INFO → R	Low	-.02*	-.0434	-.0053	.03 (95% CI =
	High	.00 ^{ns}	-.0091	.0184	[.0050, .0531])
INFO → WB	Low	-.07*	-.1351	-.0219	.09 (95% CI =
	High	.02 ^{ns}	-.0327	.0634	[.0207, .1692])
INFO → T → WB	Low	-.11*	-.1902	-.0311	.13 (95% CI =
	High	.02 ^{ns}	-.0457	.0859	[.0289, .2329])
INFO → R → WB	Low	-.00 ^{ns}	-.0078	.0006	.00 (95% CI =
	High	.00 ^{ns}	-.0013	.0029	[-.0008, .0093])

Notes. * $p < .05$, ns: non-significant, INFO: information overload, T: trust, R: risk, WB: well-being.

sustainability ($F_{(1, 496)} = 5.53, p = .019$), indicating that information overload was significantly higher under sustainable conditions ($M = 2.78, SD = 1.19$) compared to non-sustainable conditions ($M = 2.54, SD = 1.04$). The main effect of AI capability approached significance ($F_{(1, 496)} = 3.33, p = .069$), suggesting a trend toward differences in information overload between the GPT-3.5 ($M = 2.76, SD = 1.20$) and GPT-4 ($M = 2.56, SD = 1.03$) versions.

Importantly, the interaction between sustainable trip searches and AI capability was significant ($F_{(1, 496)} = 8.53, p = .004$), indicating that the impact of sustainability on information overload varied depending on the GPT version used. This significant interaction was further examined using post hoc comparisons. Notably, within the sustainable trip searches, the mean score for GPT-3.5 ($M = 3.00, SD = 1.29$) was significantly lower than for GPT-4 ($M = 2.53, SD = 1.01; t_{(496)} = 3.426, p = .001$). Additionally, a significant difference was found when comparing non-sustainable trip searches with GPT-3.5 ($M = 2.48, SD = 1.02$) to sustainable trip searches with GPT-3.5 ($M = 3.00, SD = 1.29; t_{(496)} = -3.715, p < .001$).

4.1.5.2. Direct effects. The authors implemented the model using the PROCESS macro in R (Hayes, 2021). The study results indicate strong support for most of the hypotheses (Appendix 5). **H1** was supported, showing that searching for a sustainable experience significantly increases ($b = .40, p < .01$) information overload. **H2** was also supported, demonstrating that AI capability significantly weakens ($b = -.48, p < .01$) the positive effect of searching for a sustainable experience on information overload. Further, **H3a** was supported, revealing that information overload reduces ($b = -.36, p < .001$) well-being. In line with **H3b**, well-being significantly increases ($b = .51, p < .001$) behavioral intention.

In terms of trust, **H4a** was supported, as information overload was found to reduce ($b = -.86, p < .001$) trust. **H4b** and **H4c** were also supported, indicating that trust increases both well-being ($b = .60, p < .001$) and behavioral intention ($b = .28, p < .001$). Regarding risk, **H5a** was supported, showing that information overload increases ($b = .31, p < .001$) perceived risk. However, **H5b** was not supported, as risk did not have a significant effect ($b = -.04, p > .05$) on well-being. Lastly, **H5c** was supported, demonstrating that risk decreases ($b = -.17, p < .001$) behavioral intention.

4.1.5.3. Moderated mediation analysis. In line with **H6**, the moderated mediation model was tested by using 5000 bootstrap samples with the PROCESS macro (Hayes, 2021, Table 2). The indirect effect via information overload and trust showed a significant negative mediation effect at low AI capability ($b = -.10, 95\% \text{ CI} = [-.1824, -.0258]$), which was non-significant at high AI capability ($b = .02, 95\% \text{ CI} = [-.0401, .0806]$), with a significant moderation by AI capability (index = .12, 95% CI = [.0243, .2261]). This confirms that AI capabilities of only ChatGPT 3.5 significantly mitigate the detrimental effects of

information overload on trust. The mediation effect via information overload and risk was significant at low AI capability ($b = -.02, 95\% \text{ CI} = [-.0434, -.0053]$) but non-significant at high AI capability ($b = .00, 95\% \text{ CI} = [-.0091, .0184]$), with this effect being significantly moderated by AI capability (index = .03, 95% CI = [.0050, .0531]). This demonstrates that AI capability of only ChatGPT 3.5 moderates this relationship, reducing perceived risks. For the mediation via information overload and well-being, a significant negative mediation was observed at low AI capability ($b = -.07, 95\% \text{ CI} = [-.1351, -.0219]$), whereas the effect was non-significant at high AI capability ($b = .02, 95\% \text{ CI} = [-.0327, .0634]$), with a significant moderation by AI capability (index = .09, 95% CI = [.0207, .1692]). This emphasizes that advanced AI tools of only ChatGPT 3.5 enhance well-being by reducing cognitive strain.

The sequential mediation via information overload, trust, and well-being was significant at low AI capability ($b = -.11, 95\% \text{ CI} = [-.1902, -.0311]$) but non-significant at high AI capability ($b = .02, 95\% \text{ CI} = [-.0457, .0859]$), with this effect being significantly moderated by AI capability (index = .13, 95% CI = [.0289, .2329]). This underscores that AI capability of only ChatGPT 3.5 strengthens trust and its subsequent impact on well-being.

Finally, the sequential mediation via information overload, risk, and well-being was non-significant at both low ($b = .00, 95\% \text{ CI} = [-.0078, .0006]$) and high ($b = .00, 95\% \text{ CI} = [-.0013, .0029]$) AI capability levels, with no significant moderation by AI capability (index = .00, 95% CI = [-.0008, .0093]).

4.2. Study 2 – on-trip activities – doing groceries while on a trip

4.2.1. Research design

The authors conducted a 2x2 between-subject experiment to investigate the impact of the search for a sustainable shopping and AI capabilities on respondents' perceptions when preparing for a trip to China. The experiment was designed with two independent variables: the type of experience (sustainable vs. non-sustainable) and the AI model used (GPT-4 for high AI capability vs. GPT-3.5 for low AI capability). Participants were randomly assigned to one of four scenarios, where they were asked to seek out a sustainable shopping with the assistance of either GPT-4 or GPT-3.5. The aim was to assess how the emphasis on sustainability, combined with the AI's capability, influences participants' preferences and choices in doing groceries.

4.2.2. Sample

The authors conducted an online survey using Qualtrics as the panel provider, with a sample size of 500 participants (Appendix 1). The mean age of the respondents was 46.0 years, with a standard deviation of 17.1 years. The sample consisted of 49.2% women.

4.2.3. Measures

The authors used the same established 7-point Likert scales as in Study 1 to measure various constructs in this research (Appendix 2). Information overload was assessed using a scale adapted from Hunter et al. (2024). Well-being was measured with the Meyer-Waarden and Cloarec (2022) scale. Trust was evaluated using the McKnight et al. (1998) scale, while risk was assessed with a scale from Lijarcio et al. (2019) and Yang et al. (2018). Behavioral intention was measured with the Venkatesh et al. (2012) scale, and environmental concerns were assessed using the Schroder et al. (1967) scale.

4.2.4. Data quality

All constructs demonstrated strong psychometric properties, achieving reliability with Cronbach's alpha values greater than .70 (Appendix 2). Convergent validity was established, as the average variance extracted (AVE) for each construct exceeded .50 (Appendix 2). Discriminant validity was confirmed, with squared correlations between constructs being lower than their respective AVE values (Appendix 3).

The measurement model achieved a good fit, as indicated by the results of the confirmatory factor analysis. The chi-square value was 1204.377 with 335 degrees of freedom. The root mean square error of approximation (RMSEA) was .072, which is slightly below the commonly accepted threshold of .08. The comparative fit index (CFI) was .938, and the Tucker-Lewis index (TLI) was .930, both of which exceed the usual threshold of .90.

The authors confirmed that common method variance was not an issue (Podsakoff et al., 2003). Using the ConMET package (De Schutter, 2021), competitive models where items from two constructs loaded on the same latent variable were tested, all of which significantly worsened the fit of the measurement model (χ^2 significantly increased, $p < .001$; Appendix 4). Additionally, Harman's one-factor test (Harman, 1967) performed poorly compared to the measurement model ($p < .001$).

A post hoc power analysis using the semPower package (Jobst et al., 2021) indicated sufficient sample size for robust estimates. With an RMSEA of .072, a sample size of 500, 335 degrees of freedom, and an alpha of .05, the power was highly satisfactory ($b > .99$).

4.2.5. Results

4.2.5.1. ANOVA. The authors conducted an ANOVA to evaluate the effects of sustainable shopping searches and AI capability on information overload (Fig. 2). The results revealed no significant main effects for either sustainable shopping searches ($F_{(1, 496)} = .03, p = .87$), or AI capability ($F_{(1, 496)} = .11, p = .75$), indicating that neither of these factors independently influenced information overload. However, a significant interaction effect between sustainable shopping searches and AI capability was observed ($F_{(1, 496)} = 7.53, p = .006$). This suggests that the relationship between sustainable shopping searches and information overload was moderated by AI capability, leading to differing effects of sustainable shopping searches depending on whether GPT-3.5 (i.e., low capability) or GPT-4 (i.e., high capability) was applied.

The post hoc comparisons revealed significant effects in the interaction between sustainable shopping searches and AI capability. Specifically, when comparing AI capability under different sustainability conditions, significant differences emerged. For non-sustainable conditions, GPT-4 produced significantly higher ($M = 3.09, SD = 1.42$) information overload compared to GPT-3.5 ($M = 2.74, SD = 1.13, t_{(496)} = -2.13, p = .034$). Additionally, within GPT-4, information overload under sustainable conditions was significantly lower ($M = 2.76, SD = 1.27$) than under non-sustainable conditions ($M = 3.09, SD = 1.42, t_{(496)} = 2.09, p = .037$).

4.2.5.2. Direct effects. The authors implemented the model using the PROCESS macro in R (Hayes, 2021). The study results indicate strong support for most of the hypotheses (Appendix 5). H1 was supported, showing that searching for a sustainable experience significantly increases information overload ($b = .32, p < .05$). H2 was also supported, demonstrating that AI capability significantly weakens ($b = -.63, p <$

.01) the positive effect of searching for a sustainable experience on information overload. Further, H3a was supported, revealing that information overload reduces well-being ($b = -.30, p < .001$). In line with H3b, well-being significantly increases behavioral intention ($b = .41, p < .001$).

In terms of trust, H4a was supported, as information overload was found to reduce trust ($b = -.90, p < .001$). H4b and H4c were also supported, indicating that trust increases both well-being ($b = .65, p < .001$) and behavioral intention ($b = .39, p < .001$). Regarding risk, H5a was supported, showing that information overload increases perceived risk ($b = .22, p < .001$). However, H5b was not supported, as risk did not have a significant effect on well-being ($b = .02, p > .05$). Lastly, H5c was supported, demonstrating that risk decreases behavioral intention ($b = -.15, p < .001$).

4.2.5.3. Moderated mediation analysis. In line with H6, the moderated mediation model was tested by using 5000 bootstrap samples with the PROCESS macro (Table 3). The indirect effect via information overload and trust showed a significant negative mediation effect at low AI capability ($b = -.11, 95\% CI = [-.2262, -.0130]$), and a slightly significant positive mediation effect at high AI capability ($b = .11, 90\% CI = [.0167, .2134]$), with this effect significantly moderated by AI capability (index = .22, 95% CI = [.0708, .3942]). This suggests that advanced AI tools, such as GPT-4, can mitigate the negative effects of information overload on trust, supports the hypotheses related to trust and highlights AI's role in alleviating cognitive strain, consistent with prior findings (McKnight et al., 2011; Sweller, 1988).

The mediation effect via information overload and risk was significant at low AI capability ($b = -.01, 95\% CI = [-.0247, -.0009]$) and slightly significant at high AI capability ($b = .01, 90\% CI = [.0011, .0223]$), with this effect being significantly moderated by AI capability (index = .02, 95% CI = [.0042, .0442]). For the indirect effect via information overload effect and well-being, a significant negative mediation was observed at low AI capability ($b = -.04, 95\% CI = [-.0862, -.0039]$), and a slightly significant positive effect at high AI capability ($b = .04, 90\% CI = [.0053, .0774]$), with this effect significantly moderated by AI capability (index = .08, 95% CI = [.0203, .1509]). This demonstrates that AI capability significantly moderates the relationship, emphasizing that advanced GenAI reduces the perception of risk caused by information overload.

The sequential mediation via information overload, trust, and well-being was significant at low AI capability ($b = -.08, 95\% CI = [-.1588, -.0084]$) and slightly significant at high AI capability ($b = .07, 90\% CI = [.0109, .1468]$), with this effect being significantly moderated by AI capability (index = .15, 95% CI = [.0474, .2785]). This highlights that advanced AI tools enhance user well-being by mitigating information overload.

Finally, the sequential mediation via information overload, risk, and well-being was non-significant at both low ($b = .00, 95\% CI = [-.0011, .0025]$; 90% CI = [-.0008, .0019]) and high ($b = -.00, 95\% CI =$

Table 3
Results for the moderated mediation analysis (Study 2).

Mediators	AI capability	Effect	95% CI		90% CI		Index
			Lower	Upper	Lower	Upper	
INFO → T	Low	-.11*	-.2262	-.0130	-.2045	-.0268	.22 (95% CI = [.0708, .3942])
	High	.11†	-.0017	.2364	.0167	.2134	
INFO → R	Low	-.01*	-.0247	-.0009	-.0214	-.0021	.02 (95% CI = [.0042, .0442])
	High	.01†	-.0002	.0255	.0011	.0223	
INFO → WB	Low	-.04*	-.0862	-.0039	-.0772	-.0086	.08 (95% CI = [.0203, .1509])
	High	.04†	-.0006	.0876	.0053	.0774	
INFO → T → WB	Low	-.08*	-.1588	-.0084	-.1435	-.0184	.15 (95% CI = [.0474, .2785])
	High	.07†	-.0011	.1628	.0109	.1468	
INFO → R → WB	Low	.00 ^{ns}	-.0011	.0025	-.0008	.0019	-.00 (95% CI = [-.0045, .0023])
	High	-.00 ^{ns}	-.0024	.0012	-.0019	.0008	

Notes. * $p < .05$, † $p < .10$, ns: non-significant, INFO: information overload, T: trust, R: risk, WB: well-being.

[-.0024, .0012]; 90% CI = [-.0019, .0008]) AI capability levels, with no significant moderation by AI capability (index = -.00, 95% CI = [-.0045, .0023]). The absence of a significant moderation indicates that information overload and risk does not play a sequential mediating role to improve well-being.

5. Discussion

5.1. Discussion of key findings

This research extends work on AI-powered chatbots and information processing by spotlighting a still underexplored function of GenAI: relieving information overload in sustainability-oriented tourism and shopping. Prior studies have largely emphasized adoption drivers such as usefulness, usability, and trust (Kim et al., 2021; Rese et al., 2020). Here, GenAI is theorized and tested as an information-processing partner that filters, organizes, and contextualizes sustainability information, thereby easing cognitive strain and improving decision experiences.

Across two experiments (pre-trip planning and on-site situations), sustainability-focused searches consistently produced higher information overload, reflecting the well-known burden of excessive, complex, and conflicting choice information (Eppler & Mengis, 2004; Iyengar & Lepper, 2000). Sustainability amplifies this challenge because users must weigh additional attributes, often ambiguous or difficult to compare, alongside standard criteria such as price or convenience (Scheibehenne et al., 2010; Zhang et al., 2024). In such settings, “more information” easily becomes “less clarity.”

The central contribution lies in showing that AI capability changes how this complexity is experienced. More advanced GenAI (GPT-4) reduced perceived overload more effectively than the lower-capability system (GPT-3.5), consistent with Information Processing and Cognitive Load perspectives: when information is structured and curated, extraneous load drops and cognitive resources can be redirected toward evaluation and choice (Sweller, 1988, 2010). Put differently, capability is not just performance: it determines whether AI functions as a cognitive scaffold or becomes another source of noise (Kaplan & Haenlein, 2019).

These shifts in processing reverberate through users' psychological and relational responses. When overload rises, well-being declines, echoing work linking cognitive strain to stress and diminished comfort (Eppler & Mengis, 2004; Lindenberg & Steg, 2007). Better well-being, in turn, supports continued engagement, aligning with transformative marketing arguments that psychological comfort sustains adoption in demanding decision environments (Meyer-Waarden & Cloarec, 2022). Overload also undermines trust, as overwhelmed users lose confidence in the tool's reliability and in their own ability to judge outputs (Gefen et al., 2003; Dietvorst et al., 2015). Trust then emerges as pivotal: it not only strengthens intentions to use GenAI, as emphasized in acceptance and automation reliance research, but also contributes to psychological comfort (McKnight & Chervany, 2001; Lee & See, 2004; Ostrom et al., 2019).

Perceived risk follows a related but distinct pattern. Cognitive overload heightens uncertainty and concern, reinforcing classic views of risk as a product of limited evaluative capacity and unclear outcomes (Slovic, 1987; Featherman & Pavlou, 2003). Risk, in turn, suppresses willingness to adopt GenAI, underscoring the importance of addressing privacy and reliability concerns (Asgari & Jin, 2019; Klobas et al., 2019). Yet risk did not meaningfully erode well-being in these studies, suggesting that users may compartmentalize risk as a practical judgment while well-being depends more on whether the tool feels trustworthy and supportive overall.

The evidence suggests a broader dynamic: advanced GenAI can interrupt the “overload cascade”, buffering trust, dampening risk, and protecting well-being by transforming sprawling sustainability information into manageable structure (Hu & Krishen, 2019; Sirakaya & Woodside, 2005). This reframes GenAI as more than a convenience

technology: by lowering the cognitive cost of sustainable decisions, it can function as an eco-choice facilitator, making environmentally responsible options easier to process and therefore easier to choose.

5.2. Theoretical contributions

This research advances the theoretical understanding of GenAI-powered chatbots in sustainability-focused tourism by reframing them from “adoption technologies” to cognitive and transformative decision infrastructures. Conceptually, it brings together Information Processing and Cognitive Load Theory (Sweller, 1988), trust and reliance perspectives (McKnight et al., 2011), perceived risk (Roca et al., 2009), and transformative marketing (Sirgy, 2012) to explain how GenAI changes the experience and quality of sustainable choice, an area where existing frameworks have remained relatively thin.

A first contribution is to articulate GenAI capability as a distinct theoretical construct that is not reducible to usability or perceived usefulness. Traditional models such as TAM and UTAUT foreground performance and interface beliefs (Davis, 1989; Venkatesh et al., 2012), but they do not fully capture what makes GenAI qualitatively different: the system's ability to interpret intent, compress complexity, and adaptively structure information. We conceptualize this as cognitive scaffolding, a mechanism through which GenAI reshapes the informational environment by curating, summarizing, prioritizing, and translating sustainability attributes into decision-relevant representations (Kaplan & Haenlein, 2019). This matters in sustainability contexts precisely because the information space is heterogeneous (labels, footprint metrics, certifications, local impacts), often ambiguous, and frequently value-laden (Kim, Kim, Park, et al., 2023; Zhang et al., 2024).

Second, by embedding IPCLT into the model, the study advances a process view of human–AI decision support. Rather than treating “sustainability search” as simply another antecedent of adoption, we theorize it as a cognitive load generator that changes how users allocate attention and effort (Eppler & Mengis, 2004; Sweller, 1988). GenAI then becomes meaningful not because it provides more information, but because it improves cognitive processing efficiency, reducing extraneous load and enabling prioritization under complexity. Conceptually, this extends TAM/UTAUT by positioning information-processing efficiency and adaptive structuring as central explanatory mechanisms for acceptance in environments where decision criteria proliferate and trade-offs are difficult to compute.

Third, the paper clarifies the role of trust by moving beyond a static “belief in the system” toward trust as a psychological resource that supports coping and comfort during difficult decisions (McKnight & Chervany, 2001; McKnight et al., 2011). This connects technology trust theory with transformative marketing: when decision environments are ethically charged and cognitively taxing—as sustainability often is—trust is not only instrumental for reliance but also restorative, helping preserve well-being and sustaining engagement (Sirgy, 2012; Ostrom et al., 2021). In this framing, GenAI contributes to transformative outcomes not by persuasion alone, but by making difficult decisions feel manageable.

Fourth, the study sharpens conceptual thinking about perceived risk in GenAI adoption by treating it as decision fragility under uncertainty, rather than merely a barrier variable. Sustainability information is uniquely prone to skepticism (e.g., greenwashing concerns, opaque certifications, disputed offsets), making risk a structurally embedded feature of the choice environment (Slovic, 1987; Featherman & Pavlou, 2003). GenAI's theoretical relevance here lies in its potential to reduce interpretive uncertainty, helping users reconcile conflicting signals and understand what claims mean in context, thereby shifting risk from a vague deterrent to a manageable evaluation dimension (Roca et al., 2009).

Fifth, we contribute to the literature on over-choice by conceptualizing GenAI as a choice-architecture intermediary. Prior work shows that excessive options and attribute conflict can overwhelm users and

degrade decision confidence (Gourville & Soman, 2005a, 2005b; Iyengar & Lepper, 2000). Our conceptual advance is to specify how GenAI can intervene within over-choice environments: not by shrinking choice sets mechanically, but by reorganizing them into intelligible comparisons, highlighting decisive attributes, and making trade-offs explicit. Sustainability is not incidental in this account—it is the domain where attribute overload is especially acute, and where cognitive scaffolding has outsized value.

Sixth, the paper advances a capability-contingent view of GenAI effects by distinguishing between systems that are superficially similar (chat interfaces) but cognitively different in what they can do. Treating “chatbot” as a single category obscures meaningful variation in contextual intelligence and adaptive summarization. By conceptualizing capability differences (e.g., GPT-3.5 vs. GPT-4) as theoretically consequential, we offer a more fine-grained basis for explaining why some AI deployments function as decision aids while others risk becoming additional noise. This extends adoption models by introducing capability as a boundary condition for cognitive and relational mechanisms.

Finally, this work positions GenAI as a paradigm shift from rule-based or scripted service chatbots toward contextual, generative systems that can participate in meaning-making and evaluation (Dwivedi et al., 2024; Kaplan & Haenlein, 2019). In sustainability-focused tourism, that shift is especially significant: GenAI can align decision support with eco-preferences and sustainability criteria, effectively “translating” environmental complexity into actionable guidance. Conceptually, this reframes GenAI not only as an efficiency tool but as an eco-choice facilitator, a cognitive partner that reshapes how sustainable decisions are perceived, organized, and ultimately enacted in real-world tourism journeys.

5.3. Managerial recommendations

The results of this research offer valuable insights for travel and tourism operators, marketing and sustainability managers, emphasizing the transformative role of advanced AI tools like GPT-4 in enhancing customer experience and promoting pro-environmental, sustainable behaviors.

For the trip planning, travel and tourism operators should integrate high-capability GenAI tools, such as GPT-4, into their customer-facing systems to manage the customers’ information overload. AI-driven recommendation systems can help customers plan trips more efficiently by curating before and on-site and personalizing sustainable travel options based on individual preferences and past behavior. Then by generating user-friendly simplified structured information with clear eco-certification indicators and carbon footprint details followed by links to explore detailed offers, the cognitive overload would decrease. Interactive filters would allow users to extract relevant options based on specific sustainability criteria, such as transportation type, accommodation certification or carbon footprint.

Beyond that, travel and tourism operators should use GenAI to promote accessibility of sustainable options and to reduce perceived complexity by bundling sustainable options into easily understandable packages (e.g., Eco-friendly travel itineraries or green hotel recommendations). By minimizing the effort required to find and compare environmentally superior options (e.g., low-carbon transportation, eco-certified hotels), GenAI not only increase adoption but also lower the barriers to sustainable behavior to reduce and present eco-friendly options in a way that minimizes cognitive load. For example, they could present tailored recommendations based on users’ historical preferences or geolocation. Customized, simplified, and understandable visual aids and KPIs (e.g., emojis, green, orange, red lights, infographics or visual ratings) should emphasize the positive environmental impact of their travel choices to convey sustainability attributes quickly. GenAI-driven chatbots can serve as educational tools, providing transparent and easily digestible information about sustainability certifications, carbon footprints, and eco-friendly practices. They could explain the benefits of eco-

friendly choices and help guiding users on how to balance cost and sustainability when planning trips. To improve the understanding of sustainable travel behaviors, gamification could be used to better understand the simplified KPIs and to encourage repeat use of AI systems through reward programs for sustainable behaviors, such as discounts for choosing eco-friendly transportation.

On-trip decision support tools, such as mobile apps with GenAI, should support real-time decision making and can provide quick, reliable recommendations for eco-friendly dining, shopping, or activities to reduce the customers’ information overload. This ensures that users are guided effectively during their trips without experiencing cognitive strain. Furthermore, on-site tourism marketing managers and retailers should cooperate and leverage GenAI for personalized sustainability-focused recommendations offered in the touristic destinations to align with customer preferences and environmental concerns. For instance, dynamic messaging with AI can generate on-site real-time, targeted messages based on user interactions, highlighting relevant sustainable options.

For both pre-planning and on-site activities, travel and tourism operators should monitor and address information overload by using AI to analyze customer interactions and identify points where users may feel overwhelmed to identify the content information overload that should be minimized. The AI based customer travel applications should highlight the well-being and trust benefits of using sustainable options in marketing campaigns. For example, by giving showcase success stories of travelers enjoying hassle-free, sustainable trips with the help of AI tools. Proactive AI based customer should proactively address customer concerns by offering real-time assistance on sustainability-related questions.

By implementing these actionable recommendations, travel and tourism operators, marketers, and sustainability managers can leverage AI tools to enhance user experience, promote trust and well-being, and ultimately encourage sustainable behaviors while mitigating the challenges of information overload. These strategies align with the broader goal of making sustainability accessible and appealing to a diverse range of customers.

6. Conclusion, limitations, and future research directions

In addition to cognitive and psychological benefits, this research underlines the potential of GenAI to contribute to environmental goals. By simplifying access to relevant sustainability indicators (e.g., emissions, labels, ethical sourcing), these tools bridge the intention-behavior gap and facilitate environmentally responsible decisions in tourism. Thus, they can play a supportive role in promoting sustainable consumption as well as behaviors and reducing the environmental footprint of travel.

The studies presented have several limitations that warrant consideration. Firstly, the research relied on a 2x2 experimental design with scenarios based on U.S. participants, which may limit the generalizability of the findings to other cultural or geographic contexts. Attitudes towards sustainability and AI vary significantly across regions, and cultural differences could influence user perceptions and behaviors. Future research should explore diverse geographic and cultural samples to improve the external validity of the findings and ensure broader applicability.

Secondly, the studies focused on two specific scenarios—trip preparation to China and shopping during a trip—potentially limiting the applicability of the findings to other tourism or consumer contexts. These contexts, while illustrative, may not capture the full spectrum of decision-making scenarios encountered by travelers. Future studies could examine a wider range of tourism and consumer situations, such as leisure travel, business trips, or local community tourism, to provide a more comprehensive understanding of how AI capabilities interact with sustainability considerations.

Thirdly, the measurement of constructs such as information

overload, well-being, and trust was based on self-reported survey data. Self-reports are subject to biases such as social desirability or inaccurate self-assessment, which may impact the reliability of the findings. While validated scales were employed, they may not fully capture the dynamic and complex nature of real-world tourism experiences. To address this limitation, future research could incorporate qualitative methods, such as in-depth interviews, ethnographic studies, or diary methods, to gain richer insights into user experiences. Additionally, employing longitudinal designs could track changes in perceptions and behaviors over time, offering a more detailed understanding of how interactions with AI evolve across different stages of the travel journey.

Another limitation of the study pertains to the comprehension and efficacy of AI-enhanced chatbot interactions. Firstly, acknowledging the significance of user proficiency in utilizing AI tools, future research should incorporate participants possessing a range of AI expertise. Such diversification will facilitate a more comprehensive analysis of how variations in user proficiency influence the outcomes and effectiveness of chatbot interactions (Essel et al., 2022). Furthermore, the interface design of chatbots plays a pivotal role in fostering positive user experiences and ensuring optimal functionality. Subsequent research ought to explore different interface designs. These investigations would provide valuable insights into how various design elements impact usability and user satisfaction, thereby offering a deeper understanding of the design principles that enhance user engagement and chatbot performance (Behrooz et al., 2023).

Another key limitation lies in the artificial nature of the experimental settings. While the controlled design allowed for precise testing of hypotheses, it does not fully reflect the complexities of real-world interactions with different AI-capabilities of GenAI tools such as ChatGPT 3.5 and 4.0. Future research should conduct field experiments in real-life settings, such as live travel booking platforms or retail environments, to validate and extend the findings. These real-world studies could uncover contextual nuances and provide actionable insights into the implementation of AI technologies in practical scenarios.

Future research should incorporate multi-dimensional operationalizations of AI performance that combine cognitive facilitation with perceived recommendation utility and relevance, to offer a more comprehensive understanding of AI effectiveness in tourism decision-making contexts (Kim et al., 2021; Zhu et al., 2022).

Beyond that, while the studies identified the moderating role of AI capabilities, they did not explore the underlying mechanisms driving these effects in depth. For example, factors such as AI user interface design, personalization features, and the perceived transparency or

ethicality of AI systems could influence user perceptions (see, for example, Cloarec, 2020, 2022; Cloarec, Cadieu, & Alrabie, 2024; Cloarec et al., 2022; Cloarec et al., 2024, 2024b; Meyer-Waarden et al., 2021). Future research should investigate how these elements impact the user experience and outcomes like decision quality, emotional responses, and behavioral intentions. Additionally, exploring broader outcomes beyond information overload, such as the quality of decisions made or the emotional satisfaction derived from using AI tools, may provide a more holistic view of how AI and sustainability intersect to shape tourism-related behaviors.

Finally, although the model suggested that risk reduction would enhance well-being, empirical results showed a limited effect. This discrepancy suggests that while trust and information clarity contribute more substantially to user well-being in GenAI-supported decisions, perceived risk alone may not be a decisive factor in such contexts. Future studies should benefit from a more nuanced exploration of emotional and cognitive mediators between risk and well-being.

CRedit authorship contribution statement

Lars Meyer-Waarden: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Julien Cloarec:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Manon Ferreira:** Writing – review & editing, Writing – original draft, Conceptualization.

Impact statement

Our research offers impactful contributions by demonstrating how advanced AI, specifically AI-driven chatbots like GPT-3.5 and GPT-4, can alleviate information overload in sustainability-focused tourism. Through experiments that reveal how AI capabilities influence user experiences during different stages of travel, we provide evidence that higher AI capabilities can effectively reduce cognitive strain associated with processing sustainability-related information. By integrating cognitive load theory and advancing the understanding of AI's role in complex decision-making, our findings extend the literature on AI adoption, information processing, and sustainable tourism. This research not only highlights the potential of AI to improve decision quality but also informs the design of AI systems that enhance user well-being, trust, and decision satisfaction in information-rich environments.

Appendices.

Appendix 1

Samples characteristics (in %)

	Study 1	Study 2	US population
Gender			
Male	45.4	49.0	48
Female	53.6	49.2	50
Non-binary/Other/Prefer not to say	1.0	1.8	2
Age			
18-24	11.4	10.8	13
25-34	19.0	18.4	19
35-44	16.6	19.8	18
45-54	21.2	17.0	19
55+	31.8	34.0	31

Appendix 2

Quality of the measurement instruments.

Constructs	Study 1			Study 2		
	α	AVE	β	α	AVE	β
Information Overload* (Hunter et al., 2024)	.95	.64		.96	.69	
ChatGPT enables me to ...						
... process large amounts of information			.76			.83
... process complex information			.83			.85
... process large amounts of information prior to making a decision			.83			.85
... make the best choice among many options to choose from			.87			.86
... have more time to process the given information			.84			.86
... process journey information less hastily			.81			.82
... have more time to consider all information			.83			.86
... be less confused when I am exposed to too much information			.76			.82
... make me feel less overloaded with the large amount of information			.77			.84
... make fewer mistakes in my decision			.81			.81
... avoid wrong decisions			.72			.78
Well-being (Meyer-Waarden and Cloarec, 2022)	.93	.81		.94	.85	
ChatGPT would improve my overall quality of life			.90			.92
ChatGPT would enhance my sense of well-being			.93			.94
ChatGPT would contribute to my sense of happiness			.88			.91
Trust (McKnight et al., 1998)	.90	.75		.93	.81	
I would trust that ChatGPT is safe			.91			.92
I would trust that ChatGPT is reliable			.87			.93
I would trust that ChatGPT does not fail			.82			.85
Risk (Lijarcio et al., 2019; Yang et al., 2018)	.87	.64		.87	.63	
I am apprehensive about using ChatGPT			.70			.66
I would avoid using ChatGPT because I am not familiar with it			.84			.78
I would be reluctant to use ChatGPT technology for fear of negative consequences			.90			.94
I am concerned that ChatGPT may cause unexpected issues if it malfunctions or is misused			.74			.76
Behavioral intention (Venkatesh et al., 2012)	.95	.87		.96	.88	
In view of its advantages, I intend to use ChatGPT for various tasks in the future			.94			.95
Considering its advantages, if I had access to ChatGPT, I intend to use it for various tasks			.94			.93
I am likely to use ChatGPT for various tasks in the future						
Environmental concerns (Schroder et al., 1967)	.87	.62		.90	.70	
I am concerned about the environment			.83			.85
The condition of the environment affects the quality of my life			.84			.86
I am willing to make sacrifices to protect the environment			.75			.81
My actions impact on the environment						

*The authors reversed the measurement instruments for information overload so that the relationships with other constructs would reflect increased information overload rather than reduced information overload.

Appendix 3

Descriptive statistics and discriminant validity.

		M	SD	INFO	WB	T	R	BI	ENV
Study 1	INFO	2.66	1.12	.64					
	WB	4.58	1.58	.46	.81				
	T	4.68	1.49	.47	.63	.75			
	R	4.08	1.49	.03	.05	.07	.64		
	BI	4.89	1.58	.42	.65	.57	.12	.87	
Study 2	ENV	5.19	1.24	.17	.12	.12	.00	.15	.62
	INFO	2.91	1.28	.69					
	WB	4.43	1.71	.49	.85				
	T	4.47	1.68	.52	.68	.81			
	R	4.26	1.54	.03	.05	.08	.63		
	BI	4.75	1.72	.44	.62	.63	.11	.88	
	ENV	5.27	1.39	.07	.08	.07	.00	.10	.70

Notes. INFO: information overload, WB: well-being, T: trust, R: risk, BI: behavioral intention, ENV: environmental concerns. The lower triangular matrix represents the squared correlations, while the diagonal represents the average variance extracted.

Appendix 4

Common method variance estimation.

	Study 1			Study 2		
	χ^2	df	$\Delta\chi^2$	χ^2	df	$\Delta\chi^2$
Proposed model	1104.613	335		1204.377	335	
Alternative models						
INFO + WB	2065.399	340	960.787***	2255.430	340	1051.053***
INFO + T	1788.470	340	683.858***	2079.573	340	875.196***
INFO + R	2154.092	340	1049.480***	2236.163	340	1031.786***
INFO + BI	2424.837	340	1320.224***	2534.626	340	1330.249***
INFO + ENV	1881.537	340	776.924***	2352.246	340	1147.869***
WB + T	1299.995	340	195.382***	1514.695	340	310.318***
WB + R	2088.727	340	984.115***	2205.582	340	1001.205***
WB + BI	1488.802	340	384.189***	1818.639	340	614.262***
WB + ENV	1924.268	340	819.656***	2335.985	340	1131.608***
T + R	2060.606	340	955.993***	2144.154	340	939.777***
T + BI	1472.959	340	368.346***	1698.844	340	494.468***
T + ENV	1912.585	340	807.972***	2338.183	340	1133.806***
R + BI	2021.426	340	916.814***	2119.253	340	914.876***
R + ENV	2178.653	340	1074.041***	2474.963	340	1270.586***
BI + ENV	1923.785	340	819.173***	2300.222	340	1095.845***
Harman's single factor	4961.947	350	3857.335***	5748.678	350	4544.301***

Notes. *** $p < .001$, INFO: information overload, WB: well-being, T: trust, R: risk, BI: behavioral intention, ENV: environmental concerns.

Appendix 5

Model estimation.

	Study 1					Study 2				
	INFO	T	R	WB	BI	INFO	T	R	WB	BI
Search										
SUST	.40**					.32*				
AICAP	.08 ^{ns}					.36*				
SUST x AICAP	-.48**					-.63**				
Framework										
INFO		-.86***	.31***	-.36***			-.90***	.22***	-.30***	
T				.60***	.28***				.65***	.39***
R				-.04 ^{ns}	-.17***				.02 ^{ns}	-.15***
WB					.51***					.41***
Controls										
Gender	-.03 ^{ns}	.29**	-.07 ^{ns}	.10 ^{ns}	.02 ^{ns}	.19 ^{ns}	.15 ^{ns}	.00 ^{ns}	.23**	.08 ^{ns}
Age	-.00 ^{ns}	-.02***	.01*	-.01**	.00 ^{ns}	-.00 ^{ns}	-.01***	.01*	-.00 ^{ns}	-.00 ^{ns}
ENV	.35***	.10*	.18**	.06 ^{ns}	.15***	.24***	.10**	.03 ^{ns}	.05 ^{ns}	.12***
R ²	.19	.52	.06	.67	.71	.10	.55	.04	.71	.71

Notes. ** $p < .001$, * $p < .01$, $p < .05$, ns: non-significant, SUST: search for sustainable experiences, AICAP: AI capability, INFO: information overload, WB: well-being, T: trust, R: risk, BI: behavioral intention, ENV: environmental concerns.

Appendix 6

Scenarios (text)

GPT3.5, Sustainable, Travel Booking in China

You are planning a trip to China, and you have access to GPT3.5, an AI assistant known for its capabilities in natural language understanding and generation. Your goal is to make sustainable decisions related to your travel booking in China. You will use GPT3.5 to help you with this. Please proceed with your travel booking decisions while considering sustainability factors specific to your trip to China.

GPT3.5, Sustainable, Grocery Shopping in China

You are currently in China and need to do some grocery shopping. You have access to GPT3.5, an AI assistant known for its capabilities in natural language understanding and generation. Your objective is to make sustainable choices while shopping for groceries in China. Please use GPT3.5 for guidance in making your grocery shopping decisions with sustainability in mind in the context of China.

GPT3.5, Non-Sustainable, Travel Booking in China

You are planning a trip to China, and you have access to GPT3.5, an AI assistant known for its capabilities in natural language understanding and generation. Your goal is to make decisions related to your travel booking in China without considering sustainability factors. You will use GPT3.5 to help you with this. Please proceed with your travel booking decisions without focusing on sustainability but considering the specific aspects of your trip to China.

GPT3.5, Non-Sustainable, Grocery Shopping in China

You are currently in China and need to do some grocery shopping. You have access to GPT3.5, an AI assistant known for its capabilities in natural language understanding and generation. Your objective is to make decisions without taking sustainability into account while grocery shopping in China. Please use GPT3.5 for guidance in making your grocery shopping decisions without considering sustainability but accounting for the local context in China.

GPT4, Sustainable, Travel Booking in China

You are planning a trip to China, and you have access to GPT4, an advanced AI assistant known for its state-of-the-art natural language processing capabilities, surpassing GPT3.5. Your goal is to make sustainable decisions related to your travel booking in China. You will use GPT4, which offers even more sophisticated language understanding and generation, to assist you with this. Please proceed with your travel booking decisions while considering sustainability factors specific to your trip to China.

GPT4, Sustainable, Grocery Shopping in China

You are currently in China and need to do some grocery shopping. You have access to GPT4, an advanced AI assistant known for its state-of-the-art natural language processing capabilities, surpassing GPT3.5. Your objective is to make sustainable choices while shopping for groceries in China. Please use GPT4, which excels in language capabilities, for guidance in making your grocery shopping decisions with sustainability in mind in the context of China.

GPT4, Non-Sustainable, Travel Booking in China

You are planning a trip to China, and you have access to GPT4, an advanced AI assistant known for its state-of-the-art natural language processing capabilities, surpassing GPT3.5. Your goal is to make decisions related to your travel booking in China without considering sustainability factors. You will use GPT4, which provides more advanced language support, to help you with this. Please proceed with your travel booking decisions without focusing on sustainability but considering the specific aspects of your trip to China.

GPT4, Non-Sustainable, Grocery Shopping in China

You are currently in China and need to do some grocery shopping. You have access to GPT4, an advanced AI assistant known for its state-of-the-art natural language processing capabilities, surpassing GPT3.5. Your objective is to make decisions without taking sustainability into account while grocery shopping in China. Please use GPT4, with its enhanced language capabilities, for guidance in making your grocery shopping decisions without considering sustainability but accounting for the local context in China.

Appendix 7

Scenarios (visuals) – Examples.

GPT3.5, Sustainable, Travel Booking in China

You

Hello, GPT3.5. I'm planning a trip to China, and I want to make sustainable decisions related to my travel booking. Can you assist me with my travel booking while considering sustainability factors specific to China?

ChatGPT

Hello! I'd be happy to assist you in making sustainable travel decisions for your trip to China. Traveling sustainably involves making choices that minimize your environmental impact and support local communities. Here are some tips and factors to consider when planning your trip to China:

1. Transportation:
 - * Consider taking direct flights to reduce your carbon footprint.
 - * Use public transportation such as buses and trains within China to reduce emissions.
 - * Opt for electric or hybrid taxis when available.
 - * Explore walking and cycling options in cities to reduce the use of fossil fuels.
2. Accommodation:
 - * Choose eco-friendly or green-certified hotels that have implemented sustainable practices.
 - * Look for accommodations with energy-efficient lighting, water-saving measures, and waste reduction initiatives.
3. Sightseeing and Activities:
 - * Support local and sustainable tourism operators and guides.
 - * Visit national parks and protected areas responsibly, following all guidelines to minimize your impact.
 - * Participate in community-based tourism initiatives to support local communities.
4. Dining:
 - * Enjoy locally sourced and organic food when dining out.
 - * Avoid restaurants that serve endangered or unsustainable seafood.
 - * Carry a reusable water bottle and utensils to minimize plastic waste.
5. Shopping:
 - * Buy souvenirs and products from local artisans and markets to support local economies.
 - * Look for Fair Trade and sustainable goods when shopping for gifts.
6. Language and Cultural Respect:
 - * Learn basic Chinese phrases and customs to connect with locals and show respect for their culture.
 - * Follow local customs, such as removing your shoes before entering someone's home or a temple.
7. Waste Management:
 - * Dispose of your waste responsibly, recycling and using trash bins as appropriate.
 - * Reduce single-use plastics by bringing reusable bags and containers.
8. Wildlife and Conservation:
 - * Avoid purchasing products made from endangered species, such as ivory and rhino horn.
 - * Respect wildlife and maintain a safe distance when observing animals in the wild.
9. Carbon Offsetting:
 - * Consider offsetting your carbon emissions by supporting reputable carbon offset programs.
10. Research and Plan Ahead:
 - * Research sustainable travel options and organizations that promote responsible tourism in China.
 - * Plan your itinerary to minimize long-distance travel and reduce your carbon footprint.

Remember that every small effort counts towards making your trip more sustainable. By being mindful of your choices and their impact, you can have a positive influence on the environment and local communities during your trip to China.

*GPT4, Sustainable, Travel Booking in China***You**

Hello, GPT4. I'm planning a trip to China, and I want to make sustainable decisions related to my travel booking. Can you assist me with my travel booking while considering sustainability factors specific to China? I understand you offer advanced language capabilities.

ChatGPT

Certainly, I can provide you with guidance on making sustainable travel choices for your trip to China. Here are some key factors to consider:

Transportation

1. **Choose Greener Flights:** Look for airlines with newer, more fuel-efficient fleets or those offering carbon offset programs.
2. **Use Public Transport:** Once in China, opt for public transportation like trains and buses, which are more eco-friendly than private cars.
3. **Consider Train Travel:** For intercity travel within China, high-speed trains are an efficient and sustainable option.

Accommodation

1. **Eco-friendly Hotels:** Seek out hotels with a strong commitment to sustainability, including energy-saving measures, water conservation, and waste reduction.
2. **Local Homestays:** Staying with locals via homestays can often be more sustainable than large hotel chains.

**Activities**

1. **Eco-Tourism:** Look for eco-tourism opportunities that support conservation and local communities.
2. **Cultural Experiences:** Engage in activities that promote cultural understanding and support local artisans and traditions.

Dining

1. **Local Cuisine:** Eating locally sourced food reduces carbon footprint. Try to dine at places that use local ingredients.
2. **Avoid Over-Touristed Areas:** This can help reduce the strain on local resources and spread the economic benefits of tourism.

**General Tips**

1. **Reduce, Reuse, Recycle:** Practice these principles throughout your trip.
2. **Respect Local Customs and Environment:** Be aware of your impact on the local environment and cultural sites.
3. **Educate Yourself:** Before you go, learn about China's specific sustainability challenges and initiatives.

For specific bookings and travel arrangements, I recommend consulting with travel agencies that specialize in sustainable travel or using online platforms that have filters for eco-friendly options. Remember, sustainable travel is not just about the environment; it's also about respecting and benefiting local cultures and communities.

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