



# Influence of AI technologies on the psychology of sustainable consumption: Scoping review

Özgün Arda Kuş<sup>1\*</sup>

 0000-0002-1487-3772

<sup>1</sup> Uskudar University, Istanbul, TURKEY

\* Corresponding author: [ozgunarda.kus@uskudar.edu.tr](mailto:ozgunarda.kus@uskudar.edu.tr)

**Citation:** Kuş, Ö. A. (2026). Influence of AI technologies on the psychology of sustainable consumption: Scoping review. *Online Journal of Communication and Media Technologies*, 16(2), Article e202622. <https://doi.org/10.30935/ojcm/18275>

## ARTICLE INFO

Received: 4 Aug 2025

Accepted: 11 Mar 2026

## ABSTRACT

This scoping review maps the emerging evidence on how artificial intelligence (AI) technologies shape the psychology of sustainable consumption. Guided by Arksey and O'Malley's (2005) framework and PRISMA-ScR guidelines, a comprehensive search was conducted on June 25, 2025, using Scopus and Web of Science, combining the keywords artificial intelligence, psychology, and sustainability. There were 1,561 publications when the corpus was limited to English-language papers published between 2020 and 2025. After removing duplicates, screening titles and abstracts, and reviewing full texts, 19 research satisfied the requirements for inclusion. Using descriptive charts and inductive thematic analysis, four main things were found: (1) anthropomorphic chatbots are the most popular AI touch-point and consistently increase people's desire to buy green products; (2) AI effects are mediated by psychological states, such as social presence, hedonic motivation, perceived usefulness, and green satisfaction, rather than by technology alone; (3) algorithmic advice can be less effective than human guidance when moral or reputational stakes are high; and (4) theory building is heavily biased toward technology-acceptance models, leaving value-based and affective mechanisms under-explored. These findings highlight both the promise and the boundary conditions of AI-enabled persuasion and chart a research agenda that integrates richer motivational theories, hybrid human-AI designs, and longitudinal real-world evaluations.

**Keywords:** artificial intelligence, sustainable consumption, consumer psychology, anthropomorphic chatbots, pro-environmental behavior, psychological mediation, scoping review

## INTRODUCTION

Artificial intelligence (AI) applications, ranging from algorithmic recommendation systems to large language model chatbots, are becoming increasingly integrated into consumers' daily moments when they search, evaluate, and decide what to buy (or not to buy) (Kim & Im, 2023). A growing wave of empirical studies published since 2020 shows that these systems can nudge greener choices by reframing product attributes, personalizing eco-labels, or forecasting individual carbon footprints. Yet this emerging evidence remains dispersed across psychology, information systems, and sustainability journals, with divergent operationalization of both "AI" and "sustainable consumption" and only sporadic use of behavioral theory (e.g., technology acceptance model [TAM] [Davis, 1985] or unified theory of acceptance and use of technology [UTAUT] [Venkatesh et al., 2003]). Prior syntheses have tended to concentrate either on generic digital persuasive technologies or on the environmental impacts of AI itself, leaving unanswered how, why, and under what conditions AI interfaces reshape the cognitions, emotions, and social norms that underpin pro-environmental consumer action.

With this considered, the aim of this comprehensive review is to present the first comprehensive research map linking AI technology with sustainable consumption psychology. Using known comprehensive review techniques (Arksey & O'Malley, 2005; Levac et al., 2010; Peters et al., 2020), the topics under investigation,

areas where there are still gaps in understanding concepts and methods, and how this discipline can progress towards forming a cumulative theory have been comprehensively mapped. More specifically,

- (1) The distribution of AI techniques, psychological constructs, and consumption contexts examined to date was mapped.
- (2) The different ways in which AI interventions were found to influence people's intentions and behaviors related to sustainable consumption were brought together; and
- (3) Important gaps that need to be examined more closely, such as the lack of research on emotional mechanisms and the absence of circular economic scenarios, were highlighted.

Thus, the study establishes a fundamental agenda for researchers and practitioners aiming to leverage AI for a more sustainable consumer future.

## LITERATURE REVIEW

### AI Technologies in Consumer Decision-Making

People are choosing eco-friendly goods and services in new ways thanks to AI technology like chatbots, recommendation systems, voice assistants, and marketing tools. According to Kim and Im (2023), the human-like aspects of AI chatbots are now a key element of how customers interact with them and how their purchase habits change over time. Blut et al. (2021) did a very thorough study of 108 research papers that included 11,053 people. They discovered that five key factors (perceived intelligence, liveliness, cuteness, anthropomorphism, and social presence [SP]) have a significant impact on how people perceive objects designed to look human. Blut et al. (2021) and Klein and Martinez (2023) say that anthropomorphic cues can make objects appear warmer and more capable, but too much anthropomorphism can make them look strange and less appealing to customers. Araujo's (2018) study backs this up by showing that human-like cues like names and the way people talk, along with smart framing, make people feel like they are more socially present and anthropomorphized. This, in turn, affects the connection between design cues and emotional connection to companies.

How customizable AI systems are is another crucial thing that affects how consumers make decisions. Roy and Naidoo (2021) showed that chatbots work far better when they are made to seem like people and are utilized with the proper time orientation. Their study found that chatbots that focus on the future build more trust and satisfaction than those that focus on the present. However, this effect is different for each person (Cheng et al., 2022). This finding has important implications for sustainable consumption, as future-oriented messaging may be more effective in promoting long-term environmental benefits.

The comparison between AI recommendation systems and human recommendations reveals nuanced patterns that vary by product type and context (Puntoni et al., 2021). Castelo et al. (2019) demonstrated that consumers prefer AI recommendations for search goods but human recommendations for experience goods, with recommendation source credibility varying by product type. People think that AI is better at making utilitarian judgments, whereas humans are better at making emotional and experiential purchases. This difference is especially important when it comes to sustainable consumerism, because things typically have both functional and emotional value. Longoni et al. (2019) found that people are systematically against AI in high-stakes judgments, especially in healthcare, where people don't trust AI suggestions even when they have better performance metrics, when activities include subjective judgment, emotional labor, or personal values.

Voice characteristics and interface design are new areas of research that could have a big effect on sustainable consumption. According to Pitardi and Marriott (2021), people believe voice AI more when they think it is competent, kind, and honest. Local accents make voice AI seem more credible than standard accents. Their study found that social interaction is a big part of building trust in AI, and those who use it a lot have more trust (Pycha & Zellou, 2024). Flavián et al. (2024) built on this research and showed that recommendations from voice assistants have a big effect on whether or not people want to buy something, but the effectiveness of the recommendations depends on the type of recommendation and the characteristics of the customer. Features that made the voice sound more empathetic were shown to make people more likely to accept the app and less likely to feel like it was intruding on their lives. This suggests that emotional design elements may be especially crucial for apps that promote sustainable consumption.

The rise of GenAI apps has made it harder for consumers to make choices. Hermann and Puntoni (2024) talked about two types of GenAI: convergent thinking GenAI (for specified tasks) and divergent thinking GenAI (for creative uses). They found that consumers were more worried about authenticity, agency, and control. Their research showed that tailored marketing and consumer autonomy have big effects, with consumers being especially worried about the legitimacy of AI-generated content and their lack of control over how information is processed.

AI marketing tools have changed the way businesses interact with customers, which has big effects on promoting sustainable consumption (Marvi et al., 2025). Mustak et al. (2021) did a thorough bibliometric analysis that found eight main research areas in AI marketing. The main issues were technological acceptance and consumer behavior. Their research showed that more and more people are interested in applications for personalization, customer relationship management, and conversational commerce. Ameen et al. (2021) discovered that AI-enabled consumer experiences are affected by how useful, easy to use, and private they seem. They also found that anthropomorphic AI design makes people more interested, but it also raises ethical concerns about manipulation and transparency.

### Psychological Mechanisms of Sustainable Consumption

When mental effort is high, people grab the easy reward and skip careful comparison, so they often reject eco-friendly options even if they wanted them. Classic work shows this bias (Deck & Jahedi, 2015), and recent evidence confirms that heavy AI use can further dull deliberate thinking by off-loading effort to the machine. Gerlich (2025) found that frequent AI tool users scored lower on critical-thinking tests because they relied on the system's shortcuts, while an MIT experiment showed that ChatGPT cut "germane" cognitive load by almost half but also reduced independent reasoning. Designers should therefore pair streamlined eco-labels with short, plain explanations so that AI lowers overload without erasing reflection.

Pleasure and duty do not have to clash. Experiments show that positive emotions (fun, pride, bursts of friendly competition) increase the intention to purchase green products (Choi & Johnson, 2019). The ant forest app illustrates the point: users earn "energy" for real-world eco-acts, then watch a real tree get planted, a flow that taps joy and accomplishment and keeps millions returning (Cao & Liu, 2023). Simple emotional feedback like "you just saved 5 kg of CO<sub>2</sub>" turns a moral chore into a gratifying win.

People are more likely to act green when they think someone is watching them. That audience impact can happen with interactive virtual agents. According to a 2023 study in the *Journal of Environmental Psychology* by Yamawaki et al. (2023), a talkative avatar made people recycle more and waste less food because they were worried about how they would look. Zhong et al. (2024) say that high-status users are especially sensitive to these kinds of signals; they work harder for the environment when they know others are watching. Leaderboards, visible badges, or AI "eyes" that are visible to the public might therefore encourage straightforward, visible green actions. However, private choices may need distinct nudges.

Impression management motivation represents a significant psychological mechanism in sustainable consumption, with consumers using green consumption to project positive self-images (Otterbring et al., 2023). Folwarczny et al. (2023) show that consumers often use sustainable food choices and products as impression management tactics to increase perceived social standing and attract partners. Research shows that sustainable consumption serves three different impression management functions: status seeking, group cooperation, and peer attractiveness. All of these functions are even more pronounced in public settings. However, consumers may be perceived as engaging in "virtue signaling" if the action looks conspicuous but shallow, suggesting that impression management effects are stronger in public vs. private consumption contexts. Clear disclosure of real impact (e.g., verified carbon cuts) can help users display authenticity instead of hollow rhetoric. Silalahi (2025) adds that trust is the single strongest predictor of adopting generative-AI tools aimed at sustainable behavior. Clear explanations, privacy safeguards, and visible eco-impact metrics therefore form the backbone of any persuasive green AI system.

Lower cognitive load, pleasurable experiences, social visibility, impression management, real-time AI nudges, and strong trust all steer choices toward sustainability. None works alone: an app that is fun but confusing will still fail, and a transparent system without emotional hooks may be ignored. The most effective

designs combine these mechanisms (simple eco-points, gamified rewards, subtle social cues, and reliable AI guidance) to ensure that the sustainable option is simultaneously easy, enjoyable, and socially rewarding.

### Theoretical Frameworks in AI-Mediated Sustainability

Researchers use different hypotheses to figure out how AI technologies may help people consume in a way that is good for the environment. TAM suggests that how something useful and easy seems to be affected how people feel about it and, in turn, their intention (Davis, 1985). People use a carbon-footprint tracker if they think it will help and is easy to use. Voice or ambient interaction may even make “ease” less critical (Lu et al., 2019). UTAUT extends TAM with social influence and facilitating conditions (Venkatesh et al., 2003), while UTAUT2 adds hedonic motivation and habit (Venkatesh et al., 2012). These factors explain why a friend’s endorsement or ubiquitous smartphones raise willingness to try AI sustainability aids.

Generic models overlook AI’s autonomy and anthropomorphism, so the artificially intelligent device use acceptance (AIDUA) model adds a two-stage sequence: users first appraise hedonic value, anthropomorphism, and social influence; those appraisals elicit emotions that feed into a reasoned performance–fit judgement before intentions crystallize (Gursoy et al., 2019). A playful sustainability chatbot whose persona inspires trust may therefore outperform a sterile kiosk.

Once adoption occurs, the theory of planned behavior (TPB) argues that attitude, subjective norm, and perceived control form intentions that drive action (Ajzen, 1991). AI strengthens each lever: impact dashboards build positive attitudes, neighbor comparisons reinforce norms, and automated calculators raise perceived control. A study that linked TPB with stimulus-organism-response (S-O-R) found that “passion” and how easy an AI app was to use increased emotional value and led to long-term eco-behavior (Cao & Liu, 2023).

Value-beliefs-norms (VBN) theory adds a moral thread by linking behavior to biospheric ideals that become personal norms (Stern et al., 1999). Nguyen et al. (2026) found that an empathetic bot that shows ocean-plastic data or presents tips in language that matches people’s values can start these kinds of habits. S-O-R sees interface components as something that make people feel things like curiosity, trust, or anger, which leads to actions like looking into a low-carbon option (Mehrabian & Russell, 1974). Nudge theory (NT) targets subtle choice-architecture tweaks (Cai, 2019). AI can learn which defaults, social-proof messages, or reminders (e.g., “80 % of users chose the low-carbon item”) best shift decisions. Energy apps using such AI-driven nudges have cut real consumption (Allcott & Rogers, 2014). Transparency remains essential so users do not feel manipulated.

A socio-technical lens embeds the user, AI tool, and infrastructure in one evolving system. Rolling out AI recycling kiosks, for instance, demands municipal buy-in, worker trust, and logistics integration. Socio-technical transitions theory argues that innovations spread when technology, markets, regulation, and culture co-evolve (Geels, 2005). Feedback loops emerge: if AI recommendations boost demand for eco-products, firms retrofit supply chains, which then reshape expectations.

TAM-style constructs clarify the first “yes,” TPB and VBN unpack how use turns into action, S-O-R and nudges refine moment-to-moment design, and socio-technical analysis ensures micro-insights scale within real systems. Harnessing AI for sustainable consumption therefore demands a layered strategy that begins with individual perceptions yet recognizes the networks in which every algorithm operates.

### Contextual Factors and Implementation Challenges

AI can be a catalyst for greener lifestyles and operations, yet its influence is always shaped by context (Nishant et al., 2020). Whether an AI tool is aimed at individual consumers or at organizations profoundly alters how it must be designed, adopted, and evaluated. For consumers to be successful, they need to be motivated, find it easy, and modify their daily habits (Raman et al., 2024). For example, a phone app may encourage someone to buy eco-labeled products. An AI system, on the other hand, might keep an eye on waste on a production line. Bag et al. (2023) found that automotive manufacturing companies with strong institutional pressures and resource configurations were more likely to adopt AI for sustainable manufacturing and circular economy capabilities. Their study of 219 companies revealed that organizational flexibility and industry dynamism moderate the relationship between AI adoption and environmental performance outcomes. Metrics for greenery are also different: at home, app retention is important, but in

businesses, critical performance improvements are more important. By understanding these differences, AI designers may make sure that features, incentives, and success criteria are in line with the correct decision-makers and motivational structures (Lin et al., 2024).

Sectoral differences add another depth. AI needs to give quick, unobtrusive hints in retail, where people buy things often and don't have to think about them too much. For example, default filters that show greener products should not get in the way of the shopping process. Tourism needs deeper, trust-building interactions. Chatbots need to explain eco-certifications and persuade guests that new robots won't hurt the quality of service (Tussyadiah et al., 2020). Food apps wrestle with ingrained taste preferences, so machine-learning systems may gradually guide shoppers toward plant-based items they are likely to enjoy. Transportation applications operate with instant decisions, such as eco-route suggestions, while production platforms run long optimization cycles to minimize waste (Selvakumar & Manjunath, 2025). Regulation matters too: an energy-saving AI must respect privacy rules around smart-meter data (Raza et al., 2023), whereas in logistics it may need to comply with emissions-reporting mandates (Yin et al., 2024). No single template works across fashion, finance, or utilities; each field demands tailored psychological levers, interface styles, and compliance features. Any new technology can produce technostress, and AI is no exception. For consumers, multiple sustainability apps and constant alerts can quickly shift from helpful nudges to overwhelming "green fatigue" (Shi et al., 2024).

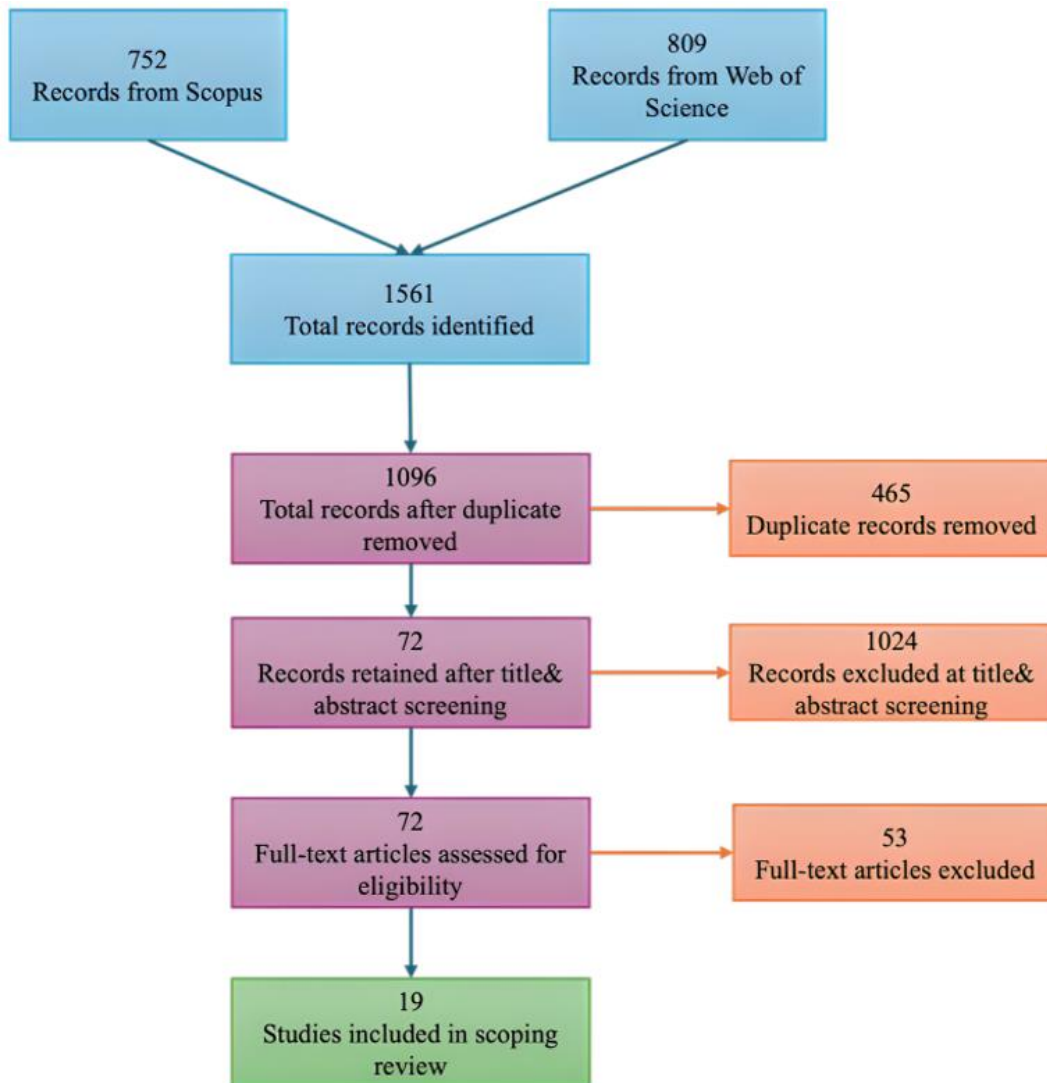
Job security is another delicate issue. When AI automates recycling lines or building-energy controls, workers may fear redundancy. Even the perception that "the algorithm will take over eventually" can erode morale and foster resistance (Zhang et al., 2022). Anxiety can be transformed into engagement with a human-centric change plan that emphasizes augmentation over replacement, outlines upskilling pathways, and involves staff in design decisions. Roles can evolve toward data-driven sustainability analysis rather than disappear, reinforcing both social and environmental dimensions of corporate responsibility (Fenwick et al., 2024).

Cultural and demographic factors further color acceptance (Chekima et al., 2015). Societies with high uncertainty avoidance might prefer human guidance over algorithmic advice, while tech-forward cultures readily embrace AI helpers (Lee & Joshi, 2020). Collectivist environments often respond to appeals that highlight communal benefits, whereas individualistic consumers look for personal gains (Barnes et al., 2024). East Asian customers, long exposed to friendly robot narratives, may trust service robots more than privacy-sensitive Westerners (Y. Li et al., 2024). Generational divides matter, too: Gen Z blends tech fluency with sustainability passion but is quick to spot greenwashing, while older users may require simpler interfaces and clearer value propositions. Effective AI therefore segments audiences and adapts content, tone, and interaction style accordingly (Vitezić & Perić, 2021).

Paradoxical outcomes must also be anticipated. Efficiency gains can trigger rebound effects: cheaper, easier services sometimes spur higher overall consumption, negating environmental savings (Mhlanga, 2025). A family whose smart-home AI slashes electricity bills might keep the lights on longer, or an e-commerce firm with ultra-efficient routing may simply ship more parcels. Moral licensing can appear as well; a shopper who buys organic produce through an AI suggestion might reward themselves with an unnecessary gadget. Moreover, AI systems consume energy—data-center footprints can undercut the very reductions they aim to create. Design solutions include feedback loops that display net impacts, user education that channels savings into further reductions, and policies that cap or price externalities (Jha et al., 2025).

Carefully engineered spillover effects can turn small wins into broader lifestyle changes. When an AI planner helps households cut food waste, it can frame that achievement as the first step on a longer journey—prompting, say, a challenge to trim energy use next month. Emphasizing green identity ("you're becoming an eco-conscious consumer!") promotes consistency across domains (Hameed et al., 2019). Social sharing features can spread norms, though they must avoid letting users treat public recognition as a license to slack elsewhere. In firms, synchronized workplace and home apps can reinforce habits both on and off the job, creating mutually reinforcing routines (Frezza, 2024).

In summary, AI's promise for sustainable consumption is real but never universal. Success depends on matching technological capabilities with the right context—consumer vs. organizational, sector-specific realities, cultural expectations, and human well-being. Designers and managers who attend to technostress,



**Figure 1.** PRISMA-ScR flow diagram (Source: Created by the author)

job security, rebound risks, and spillover potentials will harness AI as a true ally in sustainability rather than a source of unforeseen setbacks.

## MATERIALS AND METHODS

Anchored in the Arksey and O'Malley (2005) framework—subsequently refined by (Levac et al., 2010) and operationalized in the JBI manual for evidence synthesis (Peters et al., 2020)—this scoping review adopts an iterative, question-driven approach to map the breadth and conceptual contours of research on how AI technologies influence sustainable-consumption psychology. In accordance with the PRISMA-ScR reporting checklist (Tricco et al., 2018), the key study characteristics were systematically tabulated, and the findings were synthesized through descriptive mapping and inductive thematic analysis, thereby providing a transparent, reproducible, and theory-sensitive overview of the existing evidence base.

### Data Collection Process

Following the guidance of the Joanna Briggs Institute for comprehensive reviews, Scopus and Web of Science were searched using a pre-tested query that combined AI-related terms with psychological concepts and sustainable consumption keywords (see [Appendix A](#)). Filters restricted results to English-language articles published between 2020 and 2025, yielding 752 records in Scopus and 809 in WoS ([Figure 1](#)). Both lists were downloaded in .csv format, merged, and de-duplicated, removing 465 overlaps. The lead author

**Table 1.** Sectoral distribution of the studies

Primary sector	Study count	Market focus	Application context
Retail & e-commerce	4	B2C	Commercial
Tourism & hospitality	4	B2C	Commercial
Corporate & organizations	3	B2E	Organizational
Technology & AI services	3	B2C	Technology development
Consumer goods & lifestyle	3	B2C	Commercial
Marketing & digital media	2	B2B	Organizational

and a colleague with expertise in educational technology independently screened titles and abstracts, excluding studies that addressed only one—rather than both—of the focal domains (AI and sustainable consumption). At the title and abstract screening stage, initial disagreements were discussed case by case until full consensus was reached, yielding a final inter-rater agreement of 100%. This stage retained 72 papers for full-text assessment. Both reviewers then independently evaluated the full texts against the eligibility criteria; discrepancies were again resolved through discussion until complete agreement was achieved. Ultimately, 19 studies (listed in [Appendix A](#)) met all eligibility criteria and proceeded to data extraction.

## Data Analysis

A standardized data extraction form was developed to ensure systematic and transparent coding of the 19 included studies. For each study, the following variables were recorded:

- (a) bibliographic information (author(s), year, title, source, and DOI),
- (b) study aim and research questions (RQs),
- (c) sectoral context (e.g., retail and e-commerce, tourism and hospitality, and corporate and organizational) and application type (business-to-consumer [B2C], business-to-business [B2B], or business-to-employee [B2E]),
- (d) AI technology type (e.g., chatbot, GenAI, recommender system, and general AI service),
- (e) theoretical framework(s) adopted,
- (f) psychological construct(s) examined,
- (g) research methodology (quantitative, qualitative, or mixed methods),
- (h) sample characteristics (size, country, and participant profile),
- (i) data analysis technique(s) (e.g., structural equation modeling [SEM], partial least squares-structural equation modeling [PLS-SEM], and artificial neural networks [ANN]), and
- (j) key findings related to AI's influence on sustainable consumption.

A sample of the extraction form is provided in [Appendix B](#).

The extracted variables were organized in a structured spreadsheet and summarized with descriptive statistics—frequencies, cross-tabulations, and summaries. This allowed us to identify the distribution of studies according to AI technique, the theories used, psychological constructs, and the sustainable consumption domain. Guided by our RQs, the lead author and a colleague conducted a six-stage inductive thematic analysis, independently open-coding all texts and refining the codebook repeatedly until consensus was reached. Coded fragments were aggregated under higher-level themes and aligned with established behavior change frameworks to illuminate the psychological pathways through which AI interventions were seen to shape sustainable consumption intentions and actions. All analytic decisions were recorded to ensure transparency and reproducibility in line with PRISMA-ScR recommendations (Tricco et al., 2018).

## FINDINGS

### Examination of the Aims and Sectoral Distributions of Studies

Based on the analysis of study aims, the sectoral distribution reveals a balanced yet strategically focused research landscape across six primary industry sectors ([Table 1](#)). The distribution demonstrates significant concentration in consumer-facing applications while maintaining substantial representation across organizational and technological domains.

**Table 2.** Research categories and technology types

Research category	N	Technology type	Application domain
AI-enabled consumer purchase behavior	3	AI marketing, general AI	Consumer behavior
AI impact on employee environmental behavior	3	AI in organizations	Employee behavior
AI chatbots and sustainable tourism	3	Chatbots	Tourism & hospitality
AI services and pro-environmental behavior	2	General AI	Consumer behavior Info systems
GenAI and environmental information	2	GenAI	Info systems consumer behavior
AI-enabled green marketing	2	AI marketing	Marketing
AI chatbots and green purchase intention	1	Chatbots	Consumer behavior
AI chatbots and behavioral spillover	1	Chatbots	Consumer behavior
AI recommender systems and green consumption	1	Recommender systems	Consumer behavior
AI and tourism/hospitality sustainability	1	General AI	Tourism & hospitality

*Retail and e-commerce* emerge as a co-dominant sector with four studies (21.1%), encompassing fashion retail AI applications (Huong et al., 2025), sustainable product purchase intentions via chatbots (Bozdog et al., 2025), ChatGPT-powered green engagement (Sadiq et al., 2024), and AI recommender systems for green consumption (Wang et al., 2023). This sector's prominence reflects the direct intersection between AI technologies and consumer purchasing decisions, representing a critical nexus for sustainable consumption behavior intervention.

*Tourism and hospitality* share the leading position with equal representation (21.1%), featuring cross-regional tourism studies (Yang et al., 2025), chatbot-facilitated pro-environmental behavior spillover in tourism contexts (Majid et al., 2024), AI chatbot features in hospitality green satisfaction (Nguyen et al., 2026), and anthropomorphic chatbot concierges in hotel sustainability practices (Singh & Kunja, 2025). The sector's substantial representation indicates recognition of tourism's unique position in sustainability discourse and its early adoption of AI-mediated environmental behavior interventions.

*Corporate and organizational* contexts account for 15.8% of studies, examining AI impact on employee behaviors in service organizations (Low et al., 2025), organizational AI adoption and workplace pro-environmental behavior (Kim & Kim, 2025), and AI-induced job insecurity effects on workplace environmental behaviors (Kim et al., 2024). This sectoral focus reflects growing awareness of AI's complex psychological impacts within organizational sustainability frameworks.

*Technology and AI services* represent 15.8% of research, investigating AI product factors promoting pro-environmental behavior (Liao, 2025), GenAI for environmental information access (Foroughi et al., 2025), and conversational AI effectiveness in behavioral spillover (Majid et al., 2025). This sector addresses foundational questions about AI system design and implementation for sustainability outcomes.

*Consumer goods and lifestyle* make up 15.8% of studies, looking at how general AI services affect pro-environmental behavior (Guan et al., 2024) and how AI affects young consumers' decisions about sustainable consumption and lifestyle (Sharma & Sharma, 2024). This illustration shows that people understand that AI has an impact on more than just certain product categories.

The smallest area is *marketing and digital media*, which makes up 10.5% of the total. It looks into AI-enabled green marketing tactics (Sohaib et al., 2025) and live streaming with message framing for green buy intentions (Lee et al., 2025). Even though it has fewer members, this sector is important for answering important concerns regarding how to use AI to promote sustainability.

The sectoral analysis shows that the vast majority of studies focus on B2C applications (73.7%,  $n = 14$ ), followed by B2E contexts (15.8%,  $n = 3$ ), and finally B2B applications (10.5%,  $n = 2$ ). This distribution suggests that researchers are considerably more interested in how AI directly affects individual consumer behavior than in how it affects organizational or inter-business dynamics. This could be because consumer research contexts are more accessible and because changing individual behavior is perceived as a more immediate lever for sustainability transitions.

The analysis reveals distinct technology-domain alignment patterns (Table 2). Chatbots demonstrate strong specialization in specific domains, with three studies focused exclusively on tourism & hospitality (Majid et al., 2024) and two studies targeting consumer behavior applications (Bozdog et al., 2025). This suggests that chatbot technology is perceived as particularly effective for interactive, conversational interventions in service-oriented contexts.

**Table 3.** Categorization of the theories used in the studies

Category	Main point	Theories	Frequency
1. Technology-adoption logic	Explains why people accept or reject a new tool	TAM, TAM2, UTAUT, UTAUT2, AIDUA, technology-acceptance theories, DIT	12
2. Intention→action pipeline	Links attitudes, intentions, and actual behavior	TPB, PMT, S-O-R, CAB	7
3. Decision-making & cognition	Looks at how people process information and choose	RDM, BRM, RCT, CLT, ELT	6
4. Social influence & interaction	Focuses on others' presence or signals	SFT, SP, MET, ST, IMT, AT, SCT, GCT	8
5. Resource & stress lenses	Treats mental energy or resources as scarce	JD-R, CRT, COR, TT, ORT	5
6. Motivation & values for sustainability	Connects personal values to pro-green acts	VBN, ERB, GPV	4
7. Persuasion & nudge tools	Alters choice architecture rather than beliefs	NT, CBN, ELM, ST	5
8. System & structural views	Sees behavior as part of bigger human-tech setups	STST, CLT, AIDUA, IAM, CAB	7

Note. DIT: Diffusion of innovations theory; MET: Media equation theory; ST: Signaling theory; AT: Anthropomorphism theory; SCT: Social cognitive theory; & TT: Technostress theory

AI in organizations shows complete concentration within employee behavior domains (Low et al., 2025), indicating that organizational AI research maintains a clear focus on internal workplace dynamics rather than external customer-facing applications.

General AI services demonstrate the broadest domain coverage, spanning consumer behavior, information systems, and tourism & hospitality applications (Guan et al., 2024). This versatility suggests that general AI technologies are viewed as adaptable across multiple application contexts.

The research category shows research category concentration with three categories achieving maximum frequency (15.8% each): AI-enabled consumer purchase behavior, AI impact on employee environmental behavior, and AI chatbots and sustainable tourism. This tri-modal distribution indicates balanced research attention across consumer-focused, employee-focused, and tourism-specific applications, suggesting that these represent the most mature or promising research areas.

Consumer behavior emerges as the dominant application domain (42.1% of studies), appearing across six different research categories, which demonstrates the field's emphasis on understanding AI's direct influence on individual decision-making processes for sustainable consumption. Meanwhile, specialized domains like marketing (10.5%) and information systems (10.5%) maintain focused research agendas within specific technological frameworks.

The analysis reveals technology specialization trends where certain technologies align with specific research objectives. GenAI research (Foroughi et al., 2025) focuses exclusively on information processing and consumer engagement, suggesting recognition of these technologies' unique capabilities for complex information synthesis and personalized interaction. AI-enabled marketing maintains strict domain focus within marketing applications (Sohaib et al., 2025), while recommender systems appears only once (Wang et al., 2023), indicating either limited research interest or early-stage development in this technological approach for sustainability applications.

This multi-dimensional analysis demonstrates that the field exhibits both technological diversity and domain specialization, with clear patterns of technology-application alignment that suggest strategic research development rather than random distribution across possibilities.

## Theories Used in the Studies

**Table 3** shows the categorization of the theories used in the studies.

### **Technology-adoption logic (12 applications, 7 studies)**

The technology-adoption logic category dominates the theoretical landscape, representing the most frequently applied framework for understanding AI's role in sustainable consumption. UTAUT emerges as the primary theoretical choice, appearing in five studies (Low et al., 2025), while TAM appears in three studies.

This prevalence suggests researchers predominantly conceptualize AI-mediated sustainable consumption through technology acceptance lenses, focusing on perceived usefulness, ease of use, and behavioral intentions.

The concentration of technology acceptance theories indicates a foundational assumption that sustainable consumption outcomes depend primarily on users' willingness to adopt AI tools. Majid et al. (2024) demonstrate sophisticated theoretical integration by combining TAM, UTAUT, and the specialized AIDUA model, suggesting recognition that conventional TAMs may require AI-specific adaptations. The emergence of AIDUA represents theoretical evolution toward context-specific frameworks that account for unique characteristics of AI systems, such as autonomy, learning capabilities, and anthropomorphic features.

However, the dominance of adoption-focused theories may reflect a technology-centric bias that potentially overlooks deeper psychological mechanisms underlying sustainable behavior change. The frequent application of these theories suggests researchers may be prioritizing technical feasibility and user acceptance over understanding how AI systems fundamentally alter the psychology of consumption decisions.

### ***Intention-action pipeline (7 applications, 5 studies)***

This category addresses the critical gap between environmental intentions and actual sustainable behaviors, a persistent challenge in environmental psychology. TPB appears most frequently, applied in studies (Kim & Kim, 2025), indicating researchers' recognition that AI's influence on sustainable consumption must account for the complex relationship between attitudes, subjective norms, perceived behavioral control, and actual behavior.

The cognition-affect-behavior (CAB) framework's application in Huong et al. (2025) suggest researchers are exploring how AI systems might influence the cognition-affect-behavior sequence. This is particularly relevant for sustainable consumption, where emotional responses and cognitive processing often conflict with behavioral outcomes. The S-O-R framework's application in Nguyen et al. (2026) indicates attention to how AI systems function as environmental stimuli that influence internal psychological processes before manifesting in behavioral responses.

Protection motivation theory's (PMT) application in Low et al. (2025) suggests researchers are investigating how AI systems might enhance threat appraisal and coping strategies related to environmental risks. This represents a sophisticated understanding that sustainable consumption often involves managing psychological threats related to environmental degradation, and AI systems might serve as tools for threat communication and coping facilitation.

### ***Decision-making & cognition (6 applications, 3 studies)***

The cognitive processing category reveals concentrated theoretical application, with most theories appearing in Bozdog et al. (2025), which integrates rational decision-making (RDM), bounded rationality model (BRM), and rational choice theory (RCT) theories. This integration suggests researchers are explicitly comparing rational vs. bounded rationality models in AI-mediated sustainable consumption contexts. The simultaneous application of these competing decision-making theories indicates methodological sophistication in testing alternative explanatory mechanisms.

Cognitive load theory's (CLT) repeated application in Kim and Kim (2025) reflects growing attention to how AI systems affect users' cognitive resources and information processing capacity. This is particularly relevant for sustainable consumption decisions, which often require complex trade-offs between multiple criteria. The theory suggests that AI systems might either reduce cognitive load by providing simplified decision frameworks or increase cognitive burden through information overload.

Elaboration likelihood theory's (ELT) application in Lee et al. (2025) indicates researchers are exploring how different levels of explanation and detail in AI-generated recommendations affect user comprehension and decision quality. This suggests recognition that AI's effectiveness in promoting sustainable consumption depends not just on providing information, but on calibrating information complexity to users' cognitive capabilities.

### ***Social influence & interaction (8 applications, 8 studies)***

This category demonstrates remarkable theoretical diversity, with each theory appearing in a different study, suggesting researchers are exploring multiple pathways through which social dynamics influence AI-mediated sustainable consumption. The even distribution indicates that social influence mechanisms are not yet theoretically consolidated in this domain, representing an area of active theoretical exploration.

Social facilitation theory's (SFT) application in Guan et al. (2024) suggests investigation of how AI systems' presence affects individual performance in sustainable consumption tasks, potentially through social facilitation mechanisms. AT's application in Singh and Kunja (2025) indicates researchers are exploring how anthropomorphic characteristics of AI systems influence user perceptions and behaviors, suggesting that users may respond to AI systems as social agents rather than mere tools.

The application of IMT in Wang et al. (2023) and gender congruity theory (GCT) in Lata and Rana (2025) suggest researchers are investigating how different demographic groups interact with AI systems differently, and how users manage their self-presentation when using AI tools for sustainable consumption. This indicates growing recognition that AI adoption for sustainability occurs within complex social contexts where identity and social signaling play important roles.

### ***Resource & stress lenses (5 applications, 2 studies)***

This category shows concentrated application, with four of five theories appearing in Kim and Kim (2025) (job demands-resources [JD-R], TT, organizational role theory [ORT], and COR), indicating a comprehensive stress and resource perspective within organizational contexts. This concentration suggests researchers are investigating how AI implementation in organizational settings affects employee psychological resources and stress levels related to sustainable practices.

The integration of JD-R theory with technostress and conservation of resources (COR) theories indicates sophisticated understanding that AI adoption for sustainability may create competing psychological demands. Organizations implementing AI for sustainable consumption may simultaneously reduce some job demands while creating new technology-related stressors. Conservation of resources theory's (CRT) separate application in Kim et al. (2024) suggests researchers are also exploring resource conservation mechanisms at individual consumer levels.

This theoretical clustering indicates recognition that sustainable consumption enabled by AI systems occurs within resource-constrained psychological and organizational environments, where competing demands for attention, energy, and cognitive resources may influence adoption and effectiveness outcomes.

### ***Motivation & values for sustainability (4 applications, 4 studies)***

This category receives surprisingly limited theoretical attention given the sustainability focus of the research domain. VBN theory's application in Foroughi et al. (2025) suggest researchers are investigating how AI systems interact with users' environmental values, beliefs, and personal norms. The theory's dual application indicates recognition that sustainable consumption behaviors stem from deeply held value systems that AI systems must either align with or attempt to influence.

Environmentally responsible behavior's (ERB) application in Liao (2025) and green perceived value's (GPV) application in Lee et al. (2025) suggest researchers are exploring how AI systems affect perceptions of environmental responsibility and the perceived value of green consumption options. The limited representation of sustainability-specific theories may indicate a theoretical gap where established environmental psychology frameworks are underutilized in AI-mediated consumption research.

The relatively low frequency of sustainability motivation theories suggests that researchers may be prioritizing technology adoption mechanisms over understanding how AI systems fundamentally alter environmental motivation and value structures. This represents a potential area for theoretical development and empirical investigation.

### ***Persuasion & nudge tools (5 applications, 4 studies)***

The persuasion category reveals concentrated theoretical interest in how AI systems function as persuasive agents for sustainable consumption. NT appears in Sohaib et al. (2025) and Majid et al. (2025),

suggesting researchers are specifically investigating how AI systems can be designed as choice architecture tools that promote sustainable consumption without restricting user autonomy.

The combination of NT with chatbot nudging (CBN) in Sohaib et al. (2025) indicates researchers are developing AI-specific nudging frameworks that account for chatbots' and conversational agents' unique persuasive capabilities. Elaboration likelihood model's (ELM) application in Foroughi et al. (2025) suggests researchers are investigating whether AI-delivered persuasive messages are processed through central or peripheral routes, which has implications for message design and effectiveness.

ST's application in Sohaib et al. (2025) indicates attention to how AI systems' characteristics signal quality, trustworthiness, or environmental commitment to users. This suggests growing recognition that AI systems' persuasive effectiveness depends not only on message content but also on how AI system characteristics are perceived and interpreted by users.

### **System & structural views (7 applications, 4 studies)**

This category demonstrates theoretical integration across multiple studies, with CAB and CLT appearing in multiple contexts. The repeated application of these theories suggests researchers are developing systematic understanding of how AI systems function within broader socio-technical structures that shape sustainable consumption patterns.

Kim and Kim's (2025) application of multiple system-level theories (STST, CLT, and CAB) indicates comprehensive investigation of how AI implementation affects organizational systems, cognitive processes, and behavioral patterns simultaneously. STST's application suggests researchers are explicitly adopting socio-technical systems perspectives that recognize AI technologies and human users as interconnected system components.

Integrated acceptance model's (IAM) application in Foroughi et al. (2025) and AIDUA's application in Sohaib et al. (2025) suggest researchers are developing IAM that account for multiple factors simultaneously rather than focusing on isolated psychological mechanisms. This indicates theoretical evolution toward more holistic frameworks that recognize the complex interdependencies between technology characteristics, user psychology, and environmental contexts in shaping sustainable consumption outcomes.

### **Factors Related to AI**

**Table 4** shows the categorization of factors. Based on the analysis of hypotheses data, several key patterns emerge regarding the influence of AI technologies on sustainable consumption behaviors. AI technologies appear to influence sustainable consumption through both direct and indirect pathways. Direct effects are evident in multiple studies positing straightforward relationships between AI technologies (chatbots, recommenders, and marketing tools) and sustainable consumption outcomes. For example, in Huong et al. (2025), AI technology is directly hypothesized to affect perceived usefulness, which subsequently influences purchase intention for smart fashion products. Similarly, Bozdog et al. (2025) propose that AI chatbot usage directly influences environmental awareness and attitudes toward sustainable product purchases.

Mediated effects are also prevalent across the research, with many hypotheses proposing that AI's influence operates through mediating psychological factors. In Guan et al. (2024), consumer social arousal mediates the relationship between AI services and pro-environmental behavior. Singh and Kunja (2025) demonstrate that hedonic motivation and positive experience mediate the relationship between anthropomorphized chatbot concierge and willingness to participate in sustainable practices. Other important mediators include perceived usefulness (Liao, 2025), personal information security (Huong et al., 2025), and GPV (Sadiq et al., 2024).

The relationship between AI and sustainable consumption is frequently hypothesized to be moderated by various factors. Guan et al. (2024) suggest philosophical stance moderates the effect of AI services on consumer social arousal. Environmental identity appears as a moderator in Wang et al. (2023) affecting how AI recommenders influence green consumption intention. Other notable moderators include brand credibility (Sadiq et al., 2024), innovativeness (Lee et al., 2025), city size, and AI role (partner vs. servant) as seen in Yang et al. (2025).

**Table 4.** Categorization of factors

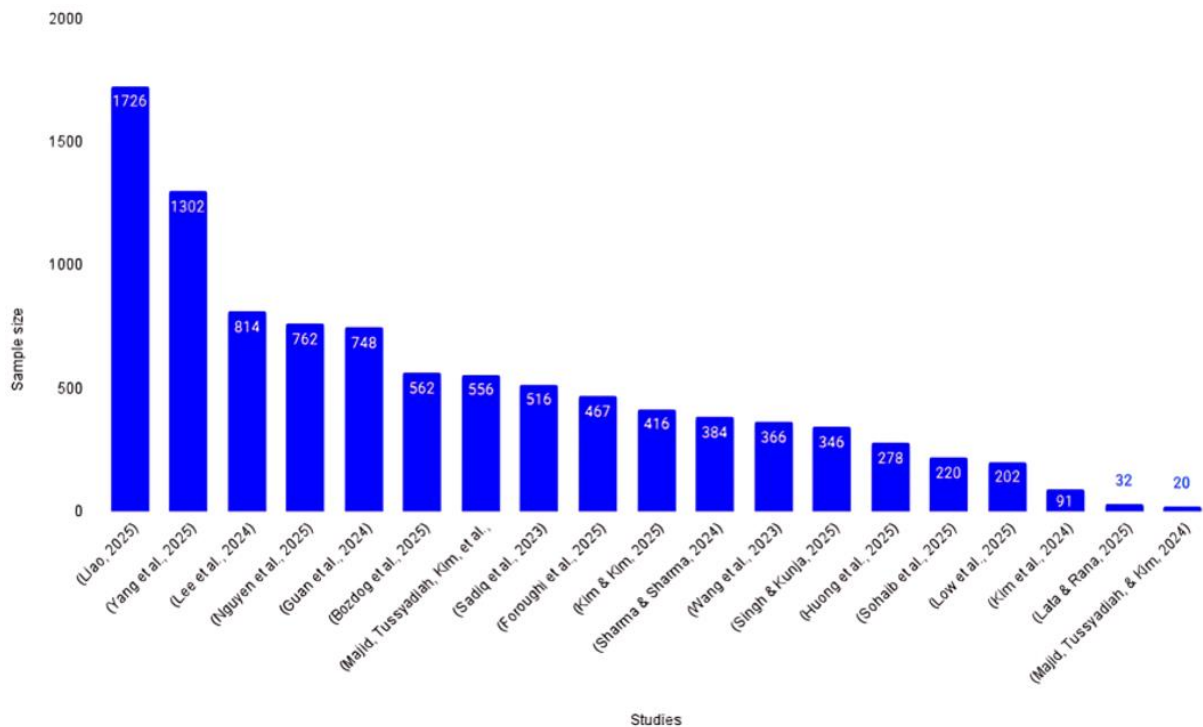
AI factor category	Specific AI factor	Mediator/moderator	Outcome variable
Technology acceptance	AI technology trust	-	Perceived usefulness, ease of use, behavioral intention
	AI performance expectancy	-	Pro-environmental behavior, green behavior
	AI effort expectancy	-	Pro-environmental behavior, green behavior
	AI self-efficacy	Perceived usefulness (M)	Behavioral intention (environmental AI)
	AI perceived usefulness	-	Behavioral intention (environmental AI)
AI chatbots	AI perceived ease of use	-	Behavioral intention (environmental AI)
	Personalized AI chatbot	-	Green satisfaction
	Empathetic AI chatbot	-	Green satisfaction
	Interactive AI chatbot	-	Green satisfaction
	Anthropomorphized chatbot	Hedonic motivation (M)	Willingness for sustainable practices
	AI chatbot usage	-	Environmental awareness, sustainable product attitudes
AI services & agents	AI chatbot (performance/effort expectancy)	-	Intention to use (sustainability)
	AI services (vs. human)	Social arousal (M)	Pro-environmental behavior
	AI recommenders (vs. human)	Environmental identity (MO)	Green consumption intention
	AI accent (standard vs. local)	Feelings of groundedness (M)	Pro-environmental intentions
AI marketing & tools	AI-powered green marketing	-	Customer trust, satisfaction, purchase intention
	Generative AI tools	-	Environmental information use
	AI-generated environmental info	-	Consumer equilibrium, green purchase intention
Workplace AI	AI adoption	Work overload (M)	Employee environmental behavior (PEBW)
	AI-induced job insecurity	Ethical leadership (MO)	Environmental behavior (negative)
	AI-driven behavioral intentions	-	Sustainable consumption behavior
	Environmental awareness	-	AI-driven behavioral intentions
	Trust in AI	-	AI-driven behavioral intentions
	Personalization perception	-	AI-driven behavioral intentions

Note. M: Mediator; MO: Moderator; & PEBW: Pro-environmental behavior at work

Several specific characteristics of AI technologies are hypothesized to influence sustainable consumption. Interface characteristics play a significant role, with studies examining AI personalization, interactivity, responsiveness, empathy, problem-solving capabilities, and SP. Nguyen et al. (2026) specifically investigate how personalized, empathetic, and interactive AI-chatbots lead to green satisfaction. Representation features are also important, with Singh and Kunja (2025) exploring AI anthropomorphizing, while Yang et al. (2025) examine AI accent (local vs. standard) and AI role (partner vs. servant). Many studies also compare AI with human agents, such as Wang et al. (2023) contrasting AI vs. human recommenders, Guan et al. (2024) comparing AI vs. human services, and Lee et al. (2025) examining AI vs. real people in live streaming.

The hypotheses suggest several key psychological mechanisms through which AI influences sustainable consumption. Cognitive factors include perceived usefulness/ease of use, effort expectancy, performance expectancy, and knowledge acquisition/application. In Low et al. (2025) effort and performance expectancy of AI usage are associated with pro-environmental and green behaviors. Social-emotional factors are also crucial, including social influence, social arousal, trust in AI, feelings of groundedness, and impression management motivation. Guan et al. (2024) specifically examine how consumer social arousal relates to pro-environmental behavior. Value-based factors appear in multiple studies, including GPV, environmental awareness, green satisfaction, personal norms, and environmental identity. Foroughi et al. (2025) explore how environmental concern, green value, and personal norms influence GenAI use for environmental information.

The analyzed hypotheses focus on several sustainable consumption outcomes. Behavioral intentions include purchase intention for green/sustainable products (Huong et al., 2025), intention to use environmentally friendly transport (Majid et al., 2025), and intention to use chatbots for sustainability. Actual behaviors studied include pro-environmental behavior, green behavior, sustainable consumption behavior,



**Figure 2.** The sample sizes of the studies (Source: Created by the author)

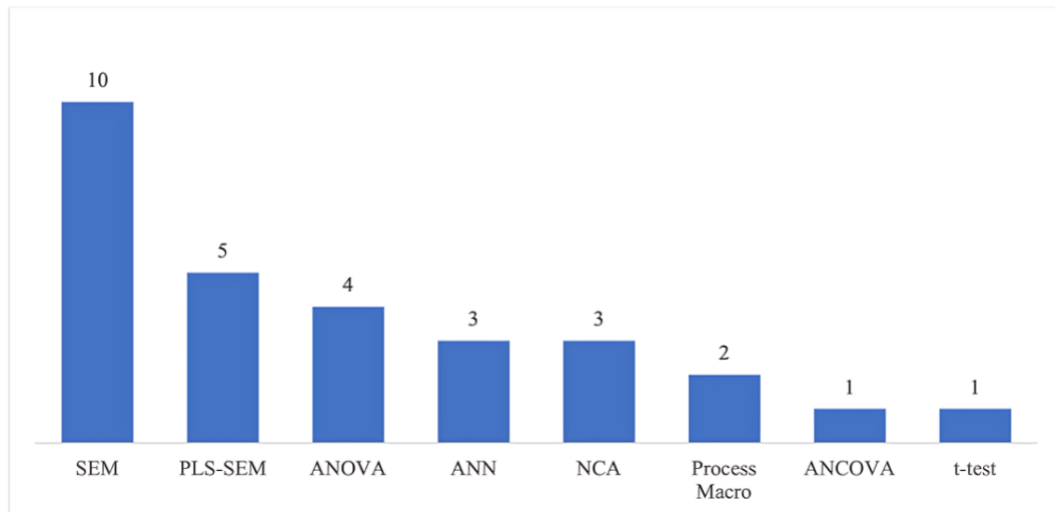
and green purchase behavior. Liao (2025) proposes that behavioral intention to use environmental AI products positively influences pro-environmental behavior. Consumer attitudes examined include green customer loyalty (Nguyen et al., 2026), green satisfaction, consumer equilibrium (Sadiq et al., 2024), and attitudes toward purchases of sustainable products.

### Methodological Analysis

The methodological examination reveals several important patterns and trends in the current research landscape. The overwhelming majority of studies (89.5%,  $n = 17$ ) employed quantitative methodologies, while only two studies (10.5%) utilized qualitative approaches. This pronounced emphasis on quantitative research reflects the field's tendency toward empirical measurement and statistical validation of relationships between AI technologies and sustainable consumption behaviors. The dominance of quantitative approaches suggests that researchers are primarily focused on establishing measurable correlations and causal relationships rather than exploring deeper contextual or experiential aspects of AI-consumer interactions.

The analysis revealed substantial variation in sample sizes across studies, ranging from 20 participants in qualitative research to 1,726 participants in the largest quantitative study (Figure 2). The total participant pool across all studies comprised 9,808 individuals, with an average sample size of 516.2 participants per study. The median sample size was 264 participants, indicating a relatively robust approach to data collection across the field. Studies with multiple experiments or sub-studies demonstrated appropriate aggregation of sample sizes, with some investigations incorporating up to four separate experimental conditions within a single research framework.

The statistical analysis techniques employed across the studies demonstrate a clear preference for advanced multivariate methods (Figure 3). SEM emerged as the most frequently utilized technique, appearing in seven studies, followed closely by PLS-SEM in six studies. Various forms of analysis of variance (ANOVA) were employed in five studies, including one-way ANOVA, ANCOVA, two-way ANOVA, and three-way ANOVA configurations. The prevalence of SEM-based approaches indicates researchers' recognition of the complex, multifaceted relationships between AI technologies and sustainable consumption psychology, requiring sophisticated analytical frameworks capable of examining multiple pathways and mediating variables simultaneously.



**Figure 3.** Analysis techniques distribution (Source: Created by the author)

Several studies demonstrated methodological innovation through hybrid approaches, particularly the integration of ANN with traditional statistical methods. Two studies specifically employed ANN methodologies, with one implementing a hybrid PLS-ANN approach, suggesting an emerging trend toward incorporating machine learning techniques in consumer behavior research. Additional sophisticated methods included necessary condition analysis (NCA), process macro by Hayes (2022) for mediation analysis, and maximum likelihood estimation procedures, indicating the field's commitment to rigorous analytical standards.

The methodological landscape reveals a mature research field characterized by sophisticated analytical approaches, substantial sample sizes, and predominantly quantitative orientations. However, the limited qualitative research suggests an opportunity for deeper exploration of consumer experiences and contextual factors influencing AI-mediated sustainable consumption behaviors. The prevalence of SEM-based methodologies reflects appropriate recognition of the complex, interconnected nature of technology adoption and environmental psychology, while the emergence of hybrid analytical approaches indicates continued methodological evolution in this rapidly developing research domain.

### Thematic Categorization Results

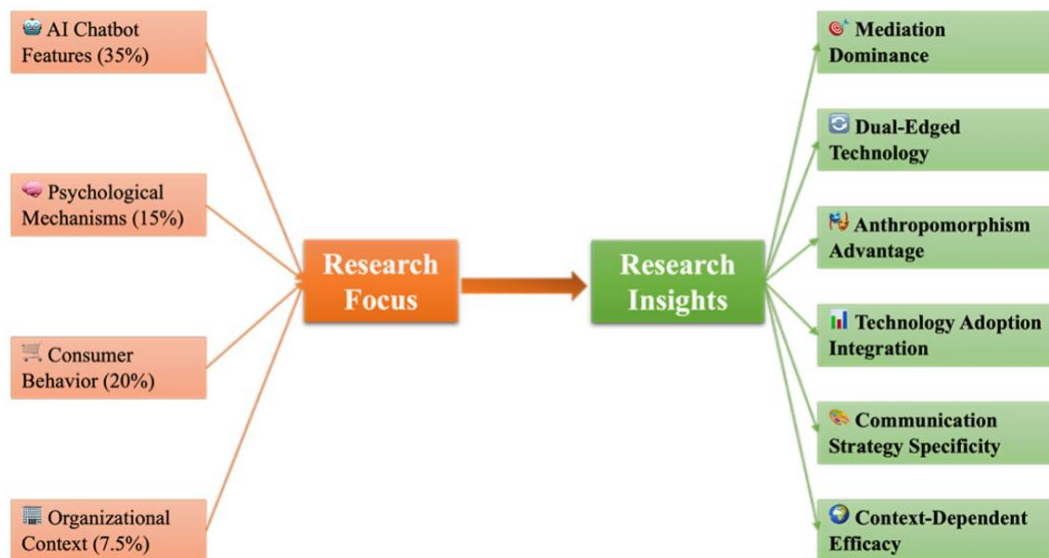
**Figure 4** depicts the concept map of the results of the studies. 19 studies reveal eight distinct thematic categories that characterize the current state of research on AI technologies and sustainable consumption psychology. The distribution demonstrates a clear research emphasis on AI chatbot features & user experience (35% of findings), followed by consumer behavior & decision making (20%) and psychological mechanisms & theories (15%).

#### *AI chatbot interface dominance*

The literature exhibits a pronounced focus on chatbot-mediated interactions, with studies consistently demonstrating that anthropomorphic features, personalization capabilities, empathy modeling, and interactive functionalities significantly influence consumer pro-environmental behaviors. Particularly notable is the finding from Yang et al. (2025) that AI utilizing local accents proves more effective than standardized approaches in promoting sustainable behavioral intentions.

#### *Mediation-centered effects*

A critical pattern emerges whereby AI technologies rarely exert direct effects on sustainable consumption behaviors. Instead, the influence operates through psychological mediators including social arousal (Guan et al., 2024), perceived usefulness and ease of use (Liao, 2025), green satisfaction (Nguyen et al., 2026), and hedonic motivation (Singh & Kunja, 2025). This mediation dependency suggests that understanding psychological pathways is essential for effective AI implementation in sustainability contexts.



**Figure 4.** Concept map of the results of the studies (Source: Created by the author)

### **Theoretical integration challenges**

The research reveals attempts to integrate traditional technology adoption frameworks (TAM and UTAUT2) with sustainability-specific constructs. However, findings from Liao (2025) indicate that direct relationships between trust, awareness, and behavioral intentions are often non-significant, requiring mediation through established technology acceptance variables.

### **Contextual Variability and Contradictions**

The corpus presents interesting contradictions regarding AI effectiveness. While multiple studies demonstrate positive AI effects on sustainable behaviors, Wang et al. (2023) reveal that AI recommenders can decrease green consumption intentions compared to human recommendations, attributed to reduced impression management motivation. This finding underscores the complexity of AI-human comparative effectiveness in sustainability contexts.

### **Organizational vs. consumer contexts**

The limited research on workplace applications (7.5% of findings) suggests different dynamics, where AI adoption creates work overload concerns that negatively impact pro-environmental workplace behaviors (Kim & Kim, 2025). However, self-efficacy in learning AI emerges as a crucial moderating factor, indicating that capability building is essential for positive organizational outcomes.

The analysis reveals several underexplored areas. First, the overwhelming focus on chatbot interfaces suggests limited investigation of other AI technologies, such as machine learning recommendation systems, computer vision applications, or predictive analytics in sustainability contexts. Second, the scarcity of organizational studies indicates an insufficient understanding of the workplace sustainability implications of AI adoption.

The theoretical landscape also requires development. While social facilitation theory and impression management theory (IMT) provide some explanatory power, the field lacks comprehensive theoretical frameworks that integrate AI technological characteristics with sustainability psychology. The emerging importance of philosophical stances (computationalism vs. dualism) as moderators (Guan et al., 2024) suggests that individual difference variables merit greater attention.

The research synthesis indicates that effective AI implementation for sustainable consumption requires careful attention to design features that enhance human-like characteristics while maintaining technological efficiency. The consistent finding that personalization, empathy, and interactivity drive positive outcomes suggests that investment in these capabilities yields measurable benefits for sustainability initiatives.

However, the evidence also suggests that practitioners must consider contextual factors and potential negative effects. The necessity for balanced AI adoption (Sharma & Sharma, 2024) and the finding that sustained behavior change requires fulfillment of multiple factors beyond technological nudging (Majid et al., 2025) indicate that AI should be viewed as one component within broader sustainability intervention strategies rather than a standalone solution.

This analysis demonstrates that while AI technologies show considerable promise for enhancing sustainable consumption psychology, their effectiveness depends critically on design characteristics, implementation context, and integration with human psychological processes. Future research should address the identified gaps while building more comprehensive theoretical frameworks to guide practical applications.

## DISCUSSION

The corpus reveals a clear gravitation toward anthropomorphic chatbots as the preferred AI conduit for promoting sustainable-consumption behavior. Conversational agents using human-like cues—like customized greetings, colloquial language, or culturally familiar avatars—performed better than more impersonal interfaces in increasing users' green attitudes and purchase intentions in more than one-third of the included research (Yang et al., 2025). Nguyen et al. (2026) and Tsai et al. (2021) consistently say that this benefit comes from a higher SP and perceived empathy. When a chatbot “sounds” or “feels” human, it activates social norms that make people more open to messages and less psychologically distant from environmental outcomes (Ni et al., 2023).

Anthropomorphic chatbots enhance user experience by mimicking human expressions and responses, creating stronger emotional connections and trust (Ma et al., 2025). However, excessive human-likeness can trigger the uncanny valley effect, causing eeriness that reduces user trust and satisfaction, particularly when users have inflated expectations of chatbot capabilities (Song & Shin, 2024). The effectiveness of anthropomorphic design is highly context-sensitive and culturally dependent (Zhao et al., 2025), requiring careful adaptation to local norms and user expectations. In environmental messaging, cultural tailoring becomes crucial, as sustainability terminology must align with regional preferences to ensure acceptance (Majid et al., 2025). Successful implementation requires balancing personality with functionality, ensuring social cues match audience expectations, and maintaining cultural appropriateness, particularly in diverse communities (Zhao et al., 2025). Anthropomorphic design remains a powerful but delicate tool requiring strategic calibration.

A recurrent pattern across the 19 studies is that AI technologies seldom alter sustainable-consumption behavior in a single leap; instead, their effects cascade through a constellation of psychological mediators. Experimental and survey evidence shows that AI services elevate pro-environmental action only after first raising social arousal, perceived usefulness/ease of use (Liao, 2025), green satisfaction (Chi & Chi, 2024), or hedonic motivation (Singh & Kunja, 2025). When these latent states are absent, the technology's direct path to behavior typically becomes non-significant (Sharma & Sharma, 2024). This finding aligns with established mediation theory, which posits that mediating variables transmit the effect of an independent variable on a dependent variable. The dominance of mediated pathways therefore suggests that sustainable consumption gains hinge on activating appropriate internal psychological states rather than relying on technological novelty alone.

This mediation-centered pattern reflects broader theoretical frameworks in consumer psychology, particularly the S-O-R model. External stimuli, such as technological and product-related factors, influence consumers' internal psychological states, which subsequently shape their behavioral responses (Wang et al., 2023). Recent research confirms that perceived value emerges as a comprehensive mediator across all predictor variables, and that pleasant experiences play a significant mediational role in connecting perceived benefits with consumers' intention to purchase environmentally friendly brands.

The prevalence of psychological mediation has important implications for both theory and practice in AI-mediated sustainability interventions. Research demonstrates that environmental attitudes, mediating 56% of effects, emerged as the strongest factor, followed by social norm perceptions (27%) and environmental self-efficacy (17%), suggesting full mediation through these psychological mechanisms (Zhang & Cat, 2025).

However, this reliance on mediation also introduces complexity and potential points of failure. While such approaches are promising and interject much needed nuance into the evaluation of behavioral results, approaches such as analysis may be difficult to implement in other research contexts (Mills et al., 2023). Furthermore, the finding that AI effects require psychological activation suggests that interventions must be carefully designed to trigger appropriate mediating states, as technological sophistication alone is insufficient to drive sustainable behavior change.

The present review uncovered important contradictory findings that challenge the prevailing narrative of AI's positive influence on sustainable consumption. Notably, Wang et al. (2023) demonstrated that AI recommendation systems can dampen green-purchase intentions compared with human advisers, with this negative effect attributed to lower impression-management motivation. This counterintuitive finding aligns with the broader phenomenon of algorithm aversion, which manifests particularly in contexts where people generally prefer human advice when it requires action, exhibiting a "human superiority effect" in decision-making contexts (Jin et al., 2025). The sustainability domain appears especially vulnerable to this aversion, as algorithms are less trusted for tasks involving moral or emotional judgment, such as ethical dilemmas or empathetic decision-making, and environmental choices often carry significant moral and reputational implications.

The role of impression management provides a crucial psychological explanation for AI's reduced effectiveness in sustainability contexts. IMT seeks to understand how individuals manage social impressions by shaping others' perceptions of themselves, as consumers consider how others might perceive their actions and may decide to take specific actions to maintain or alter their impression in the eyes of others (T.-G. Li et al., 2024). When consumers engage in sustainable consumption, they frequently do so to signal virtue, seek status, or enhance their social standing. However, the disclosure of AI agents leads to a higher propensity of consumers demonstrating unethical behavior compared to when AI agents are undisclosed, with perceived social judgment playing a crucial role in mediating this effect. This suggests that AI recommendations may diminish the social signaling value of sustainable choices, as consumers perceive less social credit for following algorithmic rather than human advice.

The situational boundaries of algorithmic credibility extend beyond impression management to encompass task characteristics and decision stakes. Research consistently shows that the more serious the consequences of a decision are, the more frequently algorithm aversion occurs, particularly in the case of very important decisions (Filiz et al., 2023). Furthermore, consumers react more favorably to human (vs. AI) recommenders when the recommended products are hedonic rather than utilitarian, expressing better product attitudes and higher purchase intentions for hedonic products (Wien & Peluso, 2021). Since sustainable consumption often involves complex value trade-offs, emotional considerations, and long-term consequences, it falls precisely into the category of decisions where human expertise is preferred. People believe human recommendations are more competent than AI recommendations for experiential products, whereas they perceive AI recommendations as more competent for material products (Jin et al., 2025), suggesting that the experiential and values-based aspects of sustainability choices inherently favor human over algorithmic guidance.

The present analysis reveals a pronounced theoretical imbalance within AI-sustainability literature, with technology-adoption models dominating the landscape while value-based and systemic frameworks remain marginalized. Technology-adoption logic, encompassing TAM, UTAUT (Venkatesh et al., 2003), and their variants, accounted for 12 applications across seven studies, representing the most frequently employed theoretical approach. In stark contrast, motivation and values for sustainability attracted merely four applications across four studies, while systemic perspectives received similarly limited attention. This theoretical concentration reflects broader limitations within technology acceptance research, where TAM and its extensions have provided invaluable insights into the determinants of technology adoption and use, but they overlook the subsequent impacts of technology use and place sustainability factors at the periphery of the research agenda (Papagiannidis & Marikyan, 2022). Furthermore, reliance on constructs like perceived ease of use and perceived usefulness rather than contextual variables conducive to particular technology use can result in overshadowing the focus on energy consumption and sustainability implications (Al-Emran & Griffy-Brown, 2023).

This theoretical skewing toward acceptance models represents a fundamental misalignment with the complexity of sustainable behavior change. VBN theory explains pro-environmental actions as stemming from personal values shaping beliefs, which then activate moral norms to act sustainably (Alshammari & Alkhwaldi, 2025), providing richer motivational explanations than simple usefulness-ease constructs. Research demonstrates that biospheric values significantly predict pro-environment beliefs, awareness of consequences, and ascription of responsibility, with personal norms serving as the prominent predictor of environmental behaviors (Al Mamun et al., 2022). Unlike TAM's focus on immediate adoption decisions, VBN theory addresses the deeper psychological foundations of environmental action, examining how values determine ecological worldview, which promotes awareness of consequences and facilitates ascription of responsibility to perform corrective actions for climate issues (Al Mamun et al., 2022; Batool et al., 2024). The limited application of such value-based frameworks in AI-sustainability research represents a significant theoretical gap, particularly given that sustainable consumption inherently involves moral considerations, long-term consequences, and identity expression that extend far beyond technological convenience.

The literature's neglect of socio-technical systems perspectives further compounds this theoretical impoverishment. Socio-technical systems theory (STST) emphasizes joint optimization of social and technical factors, recognizing that the interaction of social and technical factors creates conditions for successful organizational performance through complex, non-linear relationships (Savaget et al., 2019; Thomas, 2024). This approach acknowledges that standalone, incremental improvements are not sufficient to address current sustainability challenges, which require deep changes of sociotechnical systems involving theories on innovation systems, sustainable innovations, and system thinking (Savaget et al., 2019). The dominance of individual-level adoption models fundamentally mischaracterizes AI's role in sustainability transitions, which involves complex interactions between technological capabilities, institutional arrangements, social norms, and environmental constraints. Contemporary sociotechnical analysis recognizes progress in technologies from the perspective of ecological, financial, and socio-technical sustainability, extending conceptualizations of systems and applying core ideas to new domains beyond traditional technology focus (Bednar & Welch, 2020). Moving beyond acceptance logic toward richer motivational and socio-technical explanations would enable researchers to address how AI systems reshape the broader infrastructure of sustainable consumption rather than merely facilitating individual technology adoption decisions.

## CONCLUSION

This scoping assessment is the first to put together a full picture of how AI tools, especially anthropomorphic chatbots, relate to the psychology of sustainable consumption. By combining 19 studies that were published between 2020 and 2025, the study shows that

- (1) Conversational agents with human-like cues are the most common type of research and always increase green intentions.
- (2) AI effects mostly work through psychological pathways like SP, hedonic motivation, and perceived usefulness, not through technological novelty alone.
- (3) Algorithmic advice may not be as good as human advice when reputational stakes are high, and
- (4) Theory building is still based on technology-acceptance models, leaving value-based and affective mechanisms under-explored.

When these insights are brought together, a more nuanced and theory-sensitive agenda emerges for using AI to encourage environmentally friendly behaviors, providing designers with practical tools to maximize persuasive impact: tailored anthropomorphism, motivational framing, and hybrid human-AI endorsements.

The review's scope and timing, however, impose several limitations. First, because scoping reviews chart breadth but do not formally appraise study quality, conclusions rely on the internal rigor reported by authors. Second, restricting searches to Scopus and Web of Science, English-language articles, and the 2020-2025 window may have excluded relevant insights from other databases, grey literature, or earlier foundational work. Third, the final set of 19 studies is plenty for topic saturation, but it makes it harder to apply patterns to other situations, especially when people come from different cultures or have different tastes. Finally, the quick progress of GenAI shows that the landscape is already changing in ways that go beyond the

interventions shown here. So, future research should use longitudinal designs, look at more than one field, and use more complex theories of motivation to see if the psychologically mediated effects found in this review are real and last in real life.

**Funding:** The author received no financial support for the research and/or authorship of this article.

**Ethics declaration:** This study is a scoping review based exclusively on the analysis of previously published research. No primary data were collected from human participants, and no intervention or interaction with individuals took place. Therefore, ethical approval was not required for this research.

**AI statement:** During the preparation of this manuscript, the author used Claude (Anthropic) for grammar checking, language editing, and polishing the written text. The author reviewed and edited all AI-generated suggestions and takes full responsibility for the final content of the publication.

**Declaration of interest:** The author declared no competing interests.

**Data availability:** Data generated or analyzed during this study are available from the author on request.

## REFERENCES

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Al Mamun, A., Hayat, N., Masud, M. M., Makhbul, Z. K. M., Jannat, T., & Salleh, M. F. M. (2022). Modelling the significance of value-belief-norm theory in predicting solid waste management intention and behavior. *Frontiers in Environmental Science*, 10, Article 906002. <https://doi.org/10.3389/fenvs.2022.906002>
- Al-Emran, M., & Griffy-Brown, C. (2023). The role of technology adoption in sustainable development: Overview, opportunities, challenges, and future research agendas. *Technology in Society*, 73, Article 102240. <https://doi.org/10.1016/j.techsoc.2023.102240>
- Allcott, H., & Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104(10), 3003-3037. <https://doi.org/10.1257/aer.104.10.3003>
- Alshammari, S. H., & Alkhwaldi, A. F. (2025). An integrated approach using social support theory and technology acceptance model to investigate the sustainable use of digital learning technologies. *Scientific Reports*, 15, Article 342. <https://doi.org/10.1038/s41598-024-83450-z>
- Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, 114, Article 106548. <https://doi.org/10.1016/j.chb.2020.106548>
- Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior*, 85, 183-189. <https://doi.org/10.1016/j.chb.2018.03.051>
- Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology*, 8(1), 19-32. <https://doi.org/10.1080/1364557032000119616>
- Bag, S., Dhamija, P., Singh, R. K., Rahman, M. S., & Sreedharan, V. R. (2023). Big data analytics and artificial intelligence technologies based collaborative platform empowering absorptive capacity in health care supply chain: An empirical study. *Journal of Business Research*, 154, Article 113315. <https://doi.org/10.1016/j.jbusres.2022.113315>
- Barnes, A. J., Zhang, Y., & Valenzuela, A. (2024). AI and culture: Culturally dependent responses to AI systems. *Current Opinion in Psychology*, 58, Article 101838. <https://doi.org/10.1016/j.copsyc.2024.101838>
- Batool, N., Wani, M. D., Shah, S. A., & Dada, Z. A. (2024). Theory of planned behavior and value-belief norm theory as antecedents of pro-environmental behaviour: Evidence from the local community. *Journal of Human Behavior in the Social Environment*, 34(5), 693-709. <https://doi.org/10.1080/10911359.2023.2205912>
- Bednar, P. M., & Welch, C. (2020). Socio-technical perspectives on smart working: Creating meaningful and sustainable systems. *Information Systems Frontiers*, 22(2), 281-298. <https://doi.org/10.1007/s10796-019-09921-1>
- Blut, M., Wang, C., Wunderlich, N. V., Brock, C., Blut, M., Wang, C., Wunderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: A meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science*, 49, 632-658. <https://doi.org/10.1007/s11747-020-00762-y>

- Bozdog, L.-S., Naghi, R. I., Preda, G., & Prada, S. I. (2025). The influence of AI chatbots on the purchase intention of sustainable products. *Transformations in Business & Economics*, 24(1), 238-261. <https://doi.org/10.15388/Tibe.2025.24.1.11>
- Cai, C. W. (2019). Nudging the financial market? A review of the nudge theory. *Accounting & Finance*, 60(4), 3341-3365. <https://doi.org/10.1111/acfi.12471>
- Cao, P., & Liu, S. (2023). The impact of artificial intelligence technology stimuli on sustainable consumption behavior: Evidence from ant forest users in China. *Behavioral Sciences*, 13(7), Article 604. <https://doi.org/10.3390/bs13070604>
- Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, 56(5), 809-825. <https://doi.org/10.1177/0022243719851788>
- Chekima, B., Chekima, S., Syed Khalid Wafa, S. A. W., Igau, O. A., & Sondoh Jr, S. L. (2015). Sustainable consumption: The effects of knowledge, cultural values, environmental advertising, and demographics. *International Journal of Sustainable Development & World Ecology*, 23(2), 210-220. <https://doi.org/10.1080/13504509.2015.1114043>
- Cheng, X., Zhang, X., Cohen, J., & Mou, J. (2022). Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management*, 59(3), Article 102940. <https://doi.org/10.1016/j.ipm.2022.102940>
- Chi, N. T. K., & Chi, N. T. K. (2024). The effect of AI chatbots on pro-environment attitude and willingness to pay for environment protection. *SAGE Open*, 14(1). <https://doi.org/10.1177/21582440231226001>
- Choi, D., & Johnson, K. K. P. (2019). Influences of environmental and hedonic motivations on intention to purchase green products: An extension of the theory of planned behavior. *Sustainable Production and Consumption*, 18, 145-155. <https://doi.org/10.1016/j.spc.2019.02.001>
- Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* [PhD thesis, Massachusetts Institute of Technology].
- Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, 78, 97-119. <https://doi.org/10.1016/j.euroecorev.2015.05.004>
- Fenwick, A., Molnar, G., & Frangos, P. (2024). The critical role of HRM in AI-driven digital transformation: A paradigm shift to enable firms to move from AI implementation to human-centric adoption. *Discover Artificial Intelligence*, 4, Article 34. <https://doi.org/10.1007/s44163-024-00125-4>
- Filiz, I., Judek, J. R., Lorenz, M., & Spiwoks, M. (2023). The extent of algorithm aversion in decision-making situations with varying gravity. *PLoS ONE*, 18(2), Article e0278751. <https://doi.org/10.1371/journal.pone.0278751>
- Flavián, C., Belk, R. W., Belanche, D., & Casaló, L. V. (2024). Automated social presence in AI: Avoiding consumer psychological tensions to improve service value. *Journal of Business Research*, 175, Article 114545. <https://doi.org/10.1016/j.jbusres.2024.114545>
- Folwarczny, M., Otterbring, T., & Ares, G. (2023). Sustainable food choices as an impression management strategy. *Current Opinion in Food Science*, 49, Article 100969. <https://doi.org/10.1016/j.cofs.2022.100969>
- Foroughi, B., Naghmeh-Abbaspour, B., Wen, J., Ghobakhloo, M., Al-Emran, M., & Al-Sharafi, M. A. (2025). Determinants of generative AI in promoting green purchasing behavior: A hybrid partial least squares-artificial neural network approach. *Business Strategy and the Environment*, 34(4), 4072-4094. <https://doi.org/10.1002/bse.4186>
- Frezza, M. (2024). Spillover of sustainable routines from work to private life: Application of the identity and practice interdependence framework. *Frontiers in Psychology*, 15, Article 1420701. <https://doi.org/10.3389/fpsyg.2024.1420701>
- Geels, F. W. (2005). *Technological transitions and system innovations: A co-evolutionary and socio-technical analysis*. Edward Elgar. <https://doi.org/10.4337/9781845424596>
- Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies*, 15(1), Article 6. <https://doi.org/10.3390/soc15010006>
- Guan, B., Li, X., Luo, Z., & Liu, P. (2024). Can (A)I arouse you? The impact of AI services on consumer pro-environmental behavior. *Journal of Hospitality & Tourism Research*, 49(5), 932-945. <https://doi.org/10.1177/10963480241256602>

- Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, 49, 157-169. <https://doi.org/10.1016/j.ijinfomgt.2019.03.008>
- Hameed, I., Waris, I., & Amin Ul Haq, M. (2019). Predicting eco-conscious consumer behavior using theory of planned behavior in Pakistan. *Environmental Science and Pollution Research*, 26, 15535-15547. <https://doi.org/10.1007/s11356-019-04967-9>
- Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (3rd ed.)*. Guilford Press.
- Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research*, 180, Article 114720. <https://doi.org/10.1016/j.jbusres.2024.114720>
- Huong, N. T. T., Khanh, C. T., Hoa, H. T., Sam, P. T., Chi, N. L., An, L. M., Anh, V. P., & Minh, P. N. (2025). Impact of artificial intelligence on the purchase intention of smart fashion products. *Ianna Journal of Interdisciplinary Studies*, 7(2), 594-607. <https://doi.org/10.5281/zenodo.15501866>
- Jha, R., Jha, R., & Islam, M. (2025). Forecasting US data center CO<sub>2</sub> emissions using AI models: Emissions reduction strategies and policy recommendations. *Frontiers in Sustainability*, 5, Article 1507030. <https://doi.org/10.3389/frsus.2024.1507030>
- Jin, M., Yang, Z., Freling, T. L., & Janakiraman, N. (2025). The human superiority effect in advice taking: A multimethod exploration and implications for policy makers and governmental organizations. *Journal of Public Policy & Marketing*, 44(3), 350-369. <https://doi.org/10.1177/07439156251320314>
- Kim, B.-J., & Kim, M.-J. (2025). The AI-environment paradox: Unraveling the impact of artificial intelligence (AI) adoption on pro-environmental behavior through work overload and self-efficacy in AI learning. *Journal of Environmental Management*, 380, Article 125102. <https://doi.org/10.1016/j.jenvman.2025.125102>
- Kim, B.-J., Kim, M.-J., & Lee, J. (2024). Code green: Ethical leadership's role in reconciling AI-induced job insecurity with pro-environmental behavior in the digital workplace. *Humanities and Social Sciences Communications*, 11, Article 1627. <https://doi.org/10.1057/s41599-024-04139-2>
- Kim, J., & Im, I. (2023). Anthropomorphic response: Understanding interactions between humans and artificial intelligence agents. *Computers in Human Behavior*, 139, Article 107512. <https://doi.org/10.1016/j.chb.2022.107512>
- Klein, K., & Martinez, L. F. (2023). The impact of anthropomorphism on customer satisfaction in chatbot commerce: An experimental study in the food sector. *Electronic Commerce Research*, 23, 2789-2825. <https://doi.org/10.1007/s10660-022-09562-8>
- Lata, S., & Rana, K. (2025). AI's influence on young consumer behavior: Fostering sustainable consumption. *Young Consumers: Insight and Ideas for Responsible Marketers*, 26(5), 848-864. <https://doi.org/10.1108/yc-05-2024-2081>
- Lee, C.-C., Pan, C., & Song, Y. (2025). How live marketing affects green purchase in the age of artificial intelligence? *Emerging Markets Finance and Trade*, 61(1), 1-20. <https://doi.org/10.1080/1540496x.2023.2300654>
- Lee, K., & Joshi, K. (2020). Understanding the role of cultural context and user interaction in artificial intelligence based systems. *Journal of Global Information Technology Management*, 23(3), 171-175. <https://doi.org/10.1080/1097198x.2020.1794131>
- Levac, D., Colquhoun, H., & O'Brien, K. K. (2010). Scoping studies: Advancing the methodology. *Implementation Science*, 5, Article 69. <https://doi.org/10.1186/1748-5908-5-69>
- Li, T.-G., Zhang, C.-B., Chang, Y., & Zheng, W. (2024). The impact of AI identity disclosure on consumer unethical behavior: A social judgment perspective. *Journal of Retailing and Consumer Services*, 76, Article 103606. <https://doi.org/10.1016/j.jretconser.2023.103606>
- Li, Y., Zhou, X., Jiang, X., Fan, F., & Song, B. (2024). How service robots' human-like appearance impacts consumer trust: A study across diverse cultures and service settings. *International Journal of Contemporary Hospitality Management*, 36(9), 3151-3167. <https://doi.org/10.1108/ijchm-06-2023-0845>
- Liao, C.-H. (2025). AI product factors and pro-environmental behavior: An integrated model with hybrid analytical approaches. *Systems*, 13(3), Article 144. <https://doi.org/10.3390/systems13030144>
- Lin, J., Zeng, Y., Wu, S., & Luo, X. (2024). How does artificial intelligence affect the environmental performance of organizations? The role of green innovation and green culture. *Information & Management*, 61(2), Article 103924. <https://doi.org/10.1016/j.im.2024.103924>

- Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, 46(4), 629-650. <https://doi.org/10.1093/jcr/ucz013>
- Low, M. P., Rahim, F. A., & Wut, T. M. (2025). Leveraging artificial intelligence to foster pro-environmental and green behavior in organizations: Insights from PLS-SEM and necessary condition analysis. *Sustainable Futures*, 9, Article 100786. <https://doi.org/10.1016/j.sftr.2025.100786>
- Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, 80, 36-51. <https://doi.org/10.1016/j.ijhm.2019.01.005>
- Ma, N., Khynevyeh, R., Hao, Y., & Wang, Y. (2025). Effect of anthropomorphism and perceived intelligence in chatbot avatars of visual design on user experience: Accounting for perceived empathy and trust. *Frontiers in Computer Science*, 7, Article 1531976. <https://doi.org/10.3389/fcomp.2025.1531976>
- Majid, G. M., Tussyadiah, I., & Kim, Y. R. (2024). Exploring the potential of chatbots in extending tourists' sustainable travel practices. *Journal of Travel Research*, 64(6), 1292-1317. <https://doi.org/10.1177/00472875241247316>
- Majid, G. M., Tussyadiah, I., Kim, Y. R., & Chen, J. L. (2025). Promoting pro-environmental behaviour spillover through chatbots. *Journal of Sustainable Tourism*, 33(11), 2440-2458. <https://doi.org/10.1080/09669582.2024.2393256>
- Marvi, R., Foroudi, P., & Cuomo, M. T. (2025). Past, present and future of AI in marketing and knowledge management. *Journal of Knowledge Management*, 29(11), 1-31. <https://doi.org/10.1108/jkm-07-2023-0634>
- Mehrabian, A., & Russell, J. A. (1974). A verbal measure of information rate for studies in environmental psychology. *Environment and Behavior*, 6(2), Article 233. <https://doi.org/10.1177/001391657400600205>
- Mhlanga, D. (2025). *AI in hospital administration: Revolutionizing healthcare*. CRC Press. <https://doi.org/10.1201/9781003475804>
- Mills, S., Costa, S., & Sunstein, C. R. (2023). AI, behavioural science, and consumer welfare. *Journal of Consumer Policy*, 46(3), 387-400. <https://doi.org/10.1007/s10603-023-09547-6>
- Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research*, 124, 389-404. <https://doi.org/10.1016/j.jbusres.2020.10.044>
- Nguyen, M. T., Thach, K. T. D., Nguyen, C. N. L., Nguyen, A. C., & Doan, H. K. (2026). The influence of AI chatbots on green satisfaction and loyalty: Evidence from sustainability-driven consumer behavior. *Journal of Global Marketing*, 39(1), 103-132. <https://doi.org/10.1080/08911762.2025.2503495>
- Ni, B., Wu, F., & Huang, Q. (2023). When artificial intelligence voices human concerns: The paradoxical effects of AI voice on climate risk perception and pro-environmental behavioral intention. *International Journal of Environmental Research and Public Health*, 20(4), Article 3772. <https://doi.org/10.3390/ijerph20043772>
- Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, 53, Article 102104. <https://doi.org/10.1016/j.ijinfomgt.2020.102104>
- Otterbring, T., Gasiorowska, A., & Folwarczny, M. (2023). Editorial: Impression management strategies and environmental cues as focal factors in food research. *Frontiers in Nutrition*, 10, Article 1254856. <https://doi.org/10.3389/fnut.2023.1254856>
- Papagiannidis, S., & Marikyan, D. (2022). Environmental sustainability: A technology acceptance perspective. *International Journal of Information Management*, 63, Article 102445. <https://doi.org/10.1016/j.ijinfomgt.2021.102445>
- Peters, M. D. J., Marnie, C., Tricco, A. C., Pollock, D., Munn, Z., Alexander, L., Mclnerney, P., Godfrey, C. M., & Khalil, H. (2020). Updated methodological guidance for the conduct of scoping reviews. *JBI Evidence Synthesis*, 18(10), 2119-2126. <https://doi.org/10.11124/JBIES-20-00167>
- Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but ... Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, 38(4), 626-642. <https://doi.org/10.1002/mar.21457>
- Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing*, 85(1), 131-151. <https://doi.org/10.1177/0022242920953847>
- Pycha, A., & Zellou, G. (2024). The influence of accent and device usage on perceived credibility during interactions with voice-AI assistants. *Frontiers in Computer Science*, 6, Article 1411414. <https://doi.org/10.3389/fcomp.2024.1411414>

- Raman, R., Pattnaik, D., Lathabai, H. H., Kumar, C., Govindan, K., & Nedungadi, P. (2024). Green and sustainable AI research: An integrated thematic and topic modeling analysis. *Journal of Big Data*, 11, Article 55. <https://doi.org/10.1186/s40537-024-00920-x>
- Raza, M. H., Rind, Y. M., Javed, I., Zubair, M., Mehmood, M. Q., & Massoud, Y. (2023). Smart meters for smart energy: A review of business intelligence applications. *IEEE Access*, 11, 120001-120022. <https://doi.org/10.1109/access.2023.3326724>
- Roy, R., & Naidoo, V. (2021). Enhancing chatbot effectiveness: The role of anthropomorphic conversational styles and time orientation. *Journal of Business Research*, 126, 23-34. <https://doi.org/10.1016/j.jbusres.2020.12.051>
- Sadiq, M. W., Akhtar, M. W., Huo, C., & Zulfiqar, S. (2024). ChatGPT-powered chatbot as a green evangelist: An innovative path toward sustainable consumerism in e-commerce. *The Service Industries Journal*, 44(3-4), 173-217. <https://doi.org/10.1080/02642069.2023.2278463>
- Savaget, P., Geissdoerfer, M., Kharrazi, A., & Evans, S. (2019). The theoretical foundations of sociotechnical systems change for sustainability: A systematic literature review. *Journal of Cleaner Production*, 206, 878-892. <https://doi.org/10.1016/j.jclepro.2018.09.208>
- Selvakumar, P., & Manjunath, T. C. (2025). Food technology innovation. In Z. Hussain, A. Albattat, F. Fakir, & Z. Yi (Eds.), *Innovative trends shaping food marketing and consumption* (pp. 215-242). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3693-8542-5.ch009>
- Sharma, A. K., & Sharma, R. (2024). Assessing the influence of artificial intelligence on sustainable consumption behavior and lifestyle choices. *Young Consumers: Insight and Ideas for Responsible Marketers*, 26(5), 702-727. <https://doi.org/10.1108/yc-09-2024-2214>
- Shi, H., Shangguan, L., Dong, L., Li, M., & Zhang, Y. (2024). Voluntary vs. compulsory: Examining the consequences of two forms of employee green behaviors. *Current Psychology*, 43(26), 22297-22306. <https://doi.org/10.1007/s12144-024-05885-x>
- Silalahi, A. D. K. (2025). Can generative artificial intelligence drive sustainable behavior? A consumer-adoption model for AI-driven sustainability recommendations. *Technology in Society*, 83, Article 102995. <https://doi.org/10.1016/j.techsoc.2025.102995>
- Singh, D., & Kunja, S. R. (2025). Engaging guests for a greener tomorrow: Examining the role of hotel chatbots in encouraging pro-environmental behavior. *Tourism and Hospitality Research*. <https://doi.org/10.1177/14673584241313339>
- Sohaib, O., Alshemeili, A., & Bhatti, T. (2025). Exploring AI-enabled green marketing and green intention: An integrated PLS-SEM and NCA approach. *Cleaner and Responsible Consumption*, 17, Article 100269. <https://doi.org/10.1016/j.clrc.2025.100269>
- Song, S. W., & Shin, M. (2024). Uncanny valley effects on chatbot trust, purchase intention, and adoption intention in the context of e-commerce: The moderating role of avatar familiarity. *International Journal of Human-Computer Interaction*, 40(2), 441-456. <https://doi.org/10.1080/10447318.2022.2121038>
- Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-belief-norm theory of support for social movements: The case of environmentalism. *Human Ecology Review*, 6(2), 81-97. <https://www.humanecologyreview.org/pastissues/her62/62sternetal.pdf>
- Thomas, A. (2024). Digitally transforming the organization through knowledge management: A socio-technical system (STS) perspective. *European Journal of Innovation Management*, 27(9), 437-460. <https://doi.org/10.1108/ejim-02-2024-0114>
- Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., ... & Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine*, 169(7), 467-473. <https://doi.org/10.7326/M18-0850>
- Tsai, W.-H. S., Liu, Y., & Chuan, C.-H. (2021). How chatbots' social presence communication enhances consumer engagement: The mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing*, 15(3), 460-482. <https://doi.org/10.1108/jrim-12-2019-0200>
- Tussyadiah, I. P., Zach, F. J., & Wang, J. (2020). Do travelers trust intelligent service robots? *Annals of Tourism Research*, 81, Article 102886. <https://doi.org/10.1016/j.annals.2020.102886>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>

- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178. <https://doi.org/10.2307/41410412>
- Vitezić, V., & Perić, M. (2021). Artificial intelligence acceptance in services: Connecting with generation Z. *The Service Industries Journal*, 41(13-14), 926-946. <https://doi.org/10.1080/02642069.2021.1974406>
- Wang, K., Lu, L., Fang, J., Xing, Y., Tong, Z., & Wang, L. (2023). The downside of artificial intelligence (AI) in green choices: How AI recommender systems decrease green consumption. *Managerial and Decision Economics*, 44(6), 3346-3353. <https://doi.org/10.1002/mde.3882>
- Wien, A. H., & Peluso, A. M. (2021). Influence of human versus AI recommenders: The roles of product type and cognitive processes. *Journal of Business Research*, 137, 13-27. <https://doi.org/10.1016/j.jbusres.2021.08.016>
- Yamawaki, M., Ueda, K., Ishii, H., Shimoda, H., Ito, K., Sato, H., Fujioka, T., Sun, Q., Asa, Y., & Numata, T. (2023). Effects of virtual agent interactivity on pro-environmental behavior promotion. *Journal of Environmental Psychology*, 88, Article 101999. <https://doi.org/10.1016/j.jenvp.2023.101999>
- Yang, Y., Li, C., & Qu, Z. (2025). An AI-driven approach to sustainability: The effect of AI accent on tourists' pro-environmental behavioral intentions. *Journal of Hospitality and Tourism Management*, 63, 478-487. <https://doi.org/10.1016/j.jhtm.2025.05.012>
- Yin, Y., Wang, H., & Deng, X. (2024). Real-time logistics transport emission monitoring-Integrating artificial intelligence and internet of things. *Transportation Research Part D: Transport and Environment*, 136, Article 104426. <https://doi.org/10.1016/j.trd.2024.104426>
- Zhang, J., & Cao, A. (2025). The psychological mechanisms of education for sustainable development: Environmental attitudes, self-efficacy, and social norms as mediators of pro-environmental behavior among university students. *Sustainability*, 17(3), Article 933. <https://doi.org/10.3390/su17030933>
- Zhang, J., Zhang, Y., Lu, L., & Zhang, L. (2022). Proactive responses to job insecurity: Why and when job-insecure employees engage in political behaviors. *Management Decision*, 60(12), 3188-3208. <https://doi.org/10.1108/md-06-2021-0766>
- Zhao, X., Sun, Y., Liu, W., & Wong, C.-W. (2025). Tailoring generative AI chatbots for multiethnic communities in disaster preparedness communication: Extending the CASA paradigm. *Journal of Computer-Mediated Communication*, 30(1), Article zmae022. <https://doi.org/10.1093/jcmc/zmae022>
- Zhong, B., Niu, N., Li, J., Wu, Y., & Fan, W. (2024). Social observation modulates the influence of socioeconomic status on pro-environmental behavior: An event-related potential study. *Frontiers in Neuroscience*, 18, Article 1428659. <https://doi.org/10.3389/fnins.2024.1428659>

## APPENDIX A

Search query: (("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network\*" OR "algorithm\*" OR "automated" OR "intelligent system\*") AND ("psycholog\*" OR "behavio\*" OR "cognitive" OR "perception" OR "attitude\*" OR "intention\*" OR "decision making" OR "consumer psycholog\*") AND ("sustainable consumption" OR "green consumption" OR "eco-friendly" OR "environmental behavio\*" OR "sustainable purchas\*" OR "green purchas\*" OR "circular economy" OR "sustainability" OR "environmental psychology" OR "pro-environmental"))).

**Table A1.** Selected paper list

ID	Title	Source	Year	DOI	Citations
3	Impact of artificial intelligence on the purchase intention of smart fashion products	Ianna Journal of Interdisciplinary Studies	2025	10.5281/zenodo.15501866	Huong et al. (2025)
4	Leveraging artificial intelligence to foster pro-environmental and green behavior in organizations: Insights from PLS-SEM and necessary condition analysis	Sustainable Futures	2025	10.1016/j.sftr.2025.100786	Low et al. (2025)
5	Can (A)I arouse you? The impact of AI services on consumer pro-environmental behavior	Journal of Hospitality and Tourism Research	2025	10.1177/10963480241256602	Guan et al. (2024)
8	An AI-driven approach to sustainability: The effect of AI accent on tourists' pro-environmental behavioral intentions	Journal of Hospitality and Tourism Management	2025	10.1016/j.jhtm.2025.05.012	Yang et al. (2025)
9	AI product factors and pro-environmental behavior: An integrated model with hybrid analytical approaches	Systems	2025	10.3390/systems13030144	Liao (2025)
11	Determinants of generative AI in promoting green purchasing behavior: A hybrid partial least squares-artificial neural network approach	Business Strategy and the Environment	2025	10.1002/bse.4186	Foroughi et al. (2025)
12	Exploring AI-enabled green marketing and green intention: An integrated PLS-SEM and NCA approach	Cleaner and Responsible Consumption	2025	10.1016/j.clrc.2025.100269	Sohaib et al. (2025)
13	The AI-environment paradox: Unraveling the impact of artificial intelligence (AI) adoption on pro-environmental behavior through work overload and self-efficacy in AI learning	Journal of Environmental Management	2025	10.1016/j.jenvman.2025.125102	Kim and Kim (2025)
16	Exploring the potential of chatbots in extending tourists' sustainable travel practices	Journal of Travel Research	2025	10.1177/00472875241247316	Majid et al. (2024)
17	The influence of AI chatbots on green satisfaction and loyalty: Evidence from sustainability-driven consumer behavior	Journal of Global Marketing	2025	10.1080/08911762.2025.2503495	Nguyen et al. (2026)

**Table A1 (Continued).**

ID	Title	Source	Year	DOI	Citations
19	Engaging guests for a greener tomorrow: Examining the role of hotel chatbots in encouraging pro-environmental behavior	Tourism and Hospitality Research	2025	10.1177/14673584241313339	Singh and Kunja (2025)
22	The influence of AI chatbots on the purchase intention of sustainable products	Transformations in Business and Economics	2025	10.15388/Tibe.2025.24.1.11	Bozdog et al. (2025)
24	How live marketing affects green purchase in the age of artificial intelligence?	Emerging Markets Finance and Trade	2025	10.1080/1540496X.2023.2300654	Lee et al. (2025)
27	Code green: Ethical leadership's role in reconciling AI-induced job insecurity with pro-environmental behavior in the digital workplace	Humanities and Social Sciences Communications	2024	10.1057/s41599-024-04139-2	Kim et al. (2024)
34	Promoting pro-environmental behaviour spillover through chatbots	Journal of Sustainable Tourism	2024	10.1080/09669582.2024.2393256	Majid et al. (2025)
37	ChatGPT-powered chatbot as a green evangelist: An innovative path toward sustainable consumerism in e-commerce	Service Industries Journal	2024	10.1080/02642069.2023.2278463	Sadiq et al. (2024)
38	The downside of artificial intelligence (AI) in green choices: How AI recommender systems decrease green consumption	Managerial and Decision Economics	2023	10.1002/mde.3882	Wang et al. (2023)
41	Assessing the influence of artificial intelligence on sustainable consumption behavior and lifestyle choices	Young Consumers	2024	10.1108/YC-09-2024-2214	Sharma and Sharma (2024)
64	AI's influence on young consumer behavior: Fostering sustainable consumption	Young Consumers	2025	10.1108/YC-05-2024-2081	Lata and Rana (2025)

## APPENDIX B: DATA EXTRACTION FORM

The following standardized form (**Table B1**) was used to extract data from each of the 19 studies included. Variables were recorded in a structured spreadsheet, with one row per study and one column per variable.

**Table B1.** Data extraction form

Extracted variable	Description/coding instructions
Article ID	Unique identifier assigned to each study (e.g., S01, S02, ..., & S19)
Author(s)	Full list of authors as cited in the original publication
Year	Publication year
Title	Full title of the article
Source	Journal or conference name, volume, issue, and page numbers
DOI	Digital object identifier
Study aim/RQs	Primary objective(s) and RQ(s) as stated by the authors
Sectoral context	Industry domain: retail & e-commerce, tourism & hospitality, corporate & organizational, technology & AI services, consumer goods & lifestyle, or marketing & digital media
Application type	Business model orientation: B2C, B2B, or B2E
AI technology type	Specific AI technology examined: chatbot, GenAI, recommender system, AI-enabled marketing, general AI service, or other
Theoretical framework(s)	All theories or models adopted (e.g., TAM, UTAUT, TPB, AIDUA, S-O-R, and NT)
Theoretical category	Classified under: technology-adoption logic, intention→action pipeline, decision-making & cognition, social influence & interaction, resource & stress lenses, motivation & values, persuasion & nudge tools, or system & structural views
Psychological construct(s)	Key psychological variables measured or discussed (e.g., perceived usefulness, social presence, green satisfaction, cognitive load, and trust)
Factor category	Classified under: technology-related factors, experience-related factors, social and relational factors, or cognitive and psychological factors
Research methodology	Quantitative, qualitative, or mixed methods
Sample size	Total number of participants
Sample country/region	Geographic location of data collection
Participant profile	Demographic characteristics (e.g., university students, online consumers, hotel guests, and employees)
Data collection method	Survey, experiment, interview, content analysis, or other
Data analysis technique(s)	Statistical or analytical methods used (e.g., SEM, PLS-SEM, ANN, ANOVA, and TA)
Key findings	Main results related to the influence of AI on sustainable consumption psychology
Limitations noted	Limitations reported by the original authors

Note. All variables were coded independently by the lead author and a colleague & discrepancies were resolved through discussion until consensus was reached

