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# AI ADOPTION, TECHNOSTRESS, AND SUSTAINABLE CONSUMPTION BEHAVIOR AMONG GENERATION Z: A SYSTEMATIC LITERATURE REVIEW AND INDICATOR DEVELOPMENT

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***Abstract***
*Artificial Intelligence (AI) has been found to have a negative impact through technostress. Beyond technostress, AI can trigger continuous consumerist behavior, driven by algorithms that identify potential consumers' needs. However, the relationship between technostress and consumerist behavior, particularly among Generation Z, remains underexplored. Therefore, this study seeks to establish a framework grounded in three theoretical constructs: AI adoption derived from TAM or UTAUT, consumption behavior, and technostress. The aim is to develop a measurement instrument for a quantitative study. The literature review underpinning this study comprises 39 articles indexed in Scopus and Web of Science, identified using the search terms "AI adoption," "technostress," "sustainable consumption," and "Generation Z." The review identified 37 indicators, distributed as follows: 15 for AI adoption, 15 for technostress, and 7 for sustainable consumption behavior. These indicators serve as a robust foundation for developing a survey to gather primary data. Future empirical research will require a validation process, with Indonesian Generation Z serving as the study subjects.*
***Keywords****: AI adoption; technostress; sustainable consumption behavior; Generation Z; indicator development*

## 1. Introduction

The development of artificial intelligence (AI) has significantly transformed how consumers make decisions, how supply chains operate, and the overall landscape of digital commerce. AI has now become an integral part of everyday digital consumer experiences, as seen in features such as personalized recommendations, chatbots, predictive analytics, and smart home devices. This shift is particularly evident among Generation Z (born between 1997 and 2012), who, having grown up in a digital environment, are the most active users of AI platforms (Priporas et al., 2017) (Twenge & Campbell, 2019). However, alongside the proven utility of AI tools, a growing body of literature documents the psychological costs associated with intensive technology use—a phenomenon conceptualized as technostress. Defined as a modern adaptation disorder caused by an inability to cope with new computer technologies in a healthy manner, technostress has been operationalized into five distinct dimensions (Tarafdar et al., 2015).

The emergence of technological complexity, technological burden, technological intrusion, technological insecurity, and technological uncertainty. Existing research on technology-related stress is limited to organizational and workplace contexts (Ayyagari et al., 2011). This situation clearly indicates a relationship between technology-related stress and consumer behavior—particularly sustainable consumption—whether users are aware of it or not. Consumer behavior is already influenced by AI algorithms, whether through e-commerce shopping or social media. The influence of AI also impacts people's choices when selecting more energy-efficient electronic products equipped with smart sensors. These sustainable consumption choices also encompass environmentally and socially conscious consumption decisions (Moser, 2015), (Jaiswal & Kant, 2018).

The positive contribution of artificial intelligence—whether it facilitates or potentially undermines sustainable consumption patterns—makes theoretical sense but remains underdeveloped empirically. Artificial intelligence algorithms provide personalized sustainability information and reduce cognitive barriers to eco-friendly purchases; however, these systems can

also encourage excessive consumption through algorithmic persuasion and frictionless purchasing mechanisms (Jiménez-Barreto et al., 2022). This systematic literature review examines the relationships among these three research areas by synthesizing existing theoretical and empirical knowledge across the adoption of AI, technology stress, and sustainable consumption behavior. Specifically, this review aims to: (1) map the theoretical foundations underlying each construct; (2) identify and catalog validated measurement indicators from the peer-reviewed literature; (3) identify priority directions for future empirical research in the context of Generation Z.

## 2. Review Methodology

The integrative narrative synthesis approach is consistent with the established protocol for theory-building literature reviews in information systems and consumer behavior research (Dwivedi et al., 2019). This review protocol comprises three stages: literature search and screening, quality assessment, and thematic synthesis.

### *2.1 Search Strategy*

A systematic database search was conducted in Scopus, Web of Science (WoS), and Google Scholar using a Boolean combination of the following search terms: ("AI adoption" OR "artificial intelligence adoption" OR "technology acceptance") AND ('technostress' OR "technology stress" OR "techno-overload") AND ("sustainable consumption" OR "green purchasing" OR "eco-friendly behavior") AND ("Generation Z" OR "digital natives" OR "millennials"). A secondary search targeted each specific construct individually to ensure comprehensive coverage of the underlying theories.

### *2.2 Inclusion and Exclusion Criteria*

Articles are included if: (1) they were published in a peer-reviewed journal indexed in Scopus Q1/Q2 or Web of Science, (2) they were published between 2000 and 2024, (3) it addresses at least one of the three core constructs, and (4) it provides operationalized measurement items, validated scales, or theoretical propositions relevant to the development of indicators. Articles are excluded if they are conference proceedings, book chapters, dissertations, or gray literature, or if they do not present empirical findings or a validated theoretical framework.

### *2.3 Analysis Approach*

Thematic analysis was used to identify indicator items, theoretical relationships, and methodological insights from sources that met the criteria. An inductive coding framework was developed based on the literature and used to extract: (a) construct definitions, (b) validated measurement items, (c) antecedent and outcome variables, and (d) moderating and mediating mechanisms. The synthesized findings were organized based on three main theoretical pillars: TAM/UTAUT, the Technostress Framework, and the theory of Sustainable Consumer Behavior.

## 3. Theoretical Foundation

### *3.1 Technology Acceptance Model and UTAUT: AI Adoption Construct*

The Technology Acceptance Model (TAM), introduced by Davis (Davis, 1989), identifies perceived usefulness (PU) and perceived ease of use (PEOU) as fundamental determinants of technology adoption intentions and behavior. This two-factor model has demonstrated robust predictive validity across cultures and technologies over more than three decades of empirical research (Marangunić & Granić, 2015). In the context of AI-based consumer technologies, Perceived Usefulness (PU) relates to the extent to which AI recommendations, automated decisions, and intelligent personalization are perceived to enhance efficiency and the quality of consumption, while Perceived Ease of Use (PEOU) reflects the smoothness and intuitive nature of AI-mediated interfaces. The Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh (Venkatesh et al., 2003), unifies eight competing theories of technology acceptance into four key determinants: performance expectations, effort expectations, social influence, and supporting conditions. A consumer-oriented extension of

UTAUT, namely UTAUT (Venkatesh et al., 2012) adds hedonic motivation, perceived value, and habit as additional constructs that are highly relevant to technology use outside of organizational contexts.

A meta-analysis review by Tamilmani et al. (2021) positions UTAUT as a comprehensive technology adoption framework for consumers, synthesizing 60 UTAUT2-based studies. UTAUT is capable of explaining 52–74% of the variance in consumer behavioral intentions across various technological contexts (Benbya et al., 2021). The characteristics of AI usage which are agency-based, anthropomorphic, and probabilistic—require an expansion of the traditional TAM and UTAUT constructs by adding variables such as trust in AI, perceptions of AI intelligence, and algorithmic transparency. Longoni et al. (2019) demonstrated that resistance to AI rooted in the disregard for uniqueness—specifically, the perception that AI cannot accommodate individual heterogeneity—is a significant barrier to adoption and must be accounted for in measurement instruments (Longoni et al., 2019). A multidisciplinary synthesis that emphasizes that the adoption of AI is best understood as a multidimensional process encompassing cognitive, affective, and behavioral components (Dwivedi et al., 2021). Generation Z is the target user group for AI, characterized by "digital nativity"—an intuitive familiarity with digital devices (Lu et al., 2005). Their comfort interacting with this technology accelerates the adoption of AI, but simultaneously raises expectations for AI systems, making assessments of Perceived Ease of Use particularly crucial for this demographic group.

### *3.2* Technostress Framework Five Dimension Model

Technostress was first theorized as an adaptation disorder arising from an individual's inability to cope with computing and digital technologies. This inability to operate these technologies leads to psychological tension or stress (Brand, n.d.) (Ragu-Nathan et al., 2008) (Tarafdar et al., 2015).The operationalization of technostress that is predominant in recent research provides the measurement framework adopted in this review. Techno-overload refers to a condition in which technology forces users to work faster, process more information, and bear a higher cognitive load than they can sustain over time (Tarafdar et al., 2007). The techno-overload experienced by consumers of digital products has its own impact or burden—namely, the risk of decision-making fatigue and information overload—which arises from a ceaseless stream of notifications, recommendations, and alerts generated by AI (Ayyagari et al., 2011). Technoinvasion describes the intrusion of technology into personal time and space, creating a norm of constant availability that blurs the boundaries between work life and consumer life. Technoinvasion has negative impacts because it intrudes too deeply into personal and confidential information that can be accessed by subjective AI across these five dimensions (Throuvala et al., 2019)Technocomplexity encompasses the cognitive load arising from the perceived difficulty in learning, using, and troubleshooting technological systems (Shu et al., 2011).

In AI-mediated systems, complexity is exacerbated by the opaque nature of algorithmic processes; users often do not understand the reasoning behind specific recommendations, thereby increasing the perception of complexity beyond mere interface aspects. Techno-insecurity manifests as anxiety regarding the potential loss of jobs, the obsolescence of skills, and a loss of competitiveness in a technology-intensive environment (Tarafdar et al., 2015). Although traditionally studied in the context of employment, techno-insecurity is now increasingly relevant to consumers as AI automates consultative, creative, and analytical functions—tasks that previously required human expertise. Finally, techno-uncertainty encompasses the disorientation and anxiety triggered by rapid technological change, which causes established competencies to become obsolete quickly (Salanova et al., 2013).

Resource Conservation Theory provides a theoretical framework for understanding how technostress negatively impacts sustained behavior. This theory posits that individuals are motivated to acquire, maintain, and protect valuable resources, including cognitive capacity, emotional energy, time, and identity. Technostress depletes these resources through continuous

demands and uncertainty, thereby triggering resource-conservation behaviors that may involve disengaging cognitively from complex, multi-criteria decision-making tasks, such as evaluating sustainable consumption.

### *3.3 Sustainable Consumption Behavior: Theory and Measurement*

Sustainable consumption behavior is defined as a pattern of consumption activities that meets current needs without compromising the ability of future generations to meet their own needs. In the literature on consumer behavior, SCB has been operationalized into four main dimensions of environmentally friendly purchasing behavior: choosing environmentally certified or low-impact products; ethical consumption, which involves preferring socially responsible brands and fair-trade products; participation in the sharing economy by using the "product-as-a-service" model to reduce resource consumption; and waste minimization through reduction, reuse, and recycling of consumption outputs (Bocken et al., 2014) (Maniatis, 2016). The Theory of Planned Behavior is the most frequently applied framework for predicting eco-friendly purchasing intentions; meta-analysis evidence confirms that attitudes toward sustainable consumption, subjective norms related to sustainability, and perceived behavioral control collectively explain between 40% and 68% of the variance in eco-friendly purchasing intentions (Ajzen, 1991) (Follows & Jobber, 2000).

The Theory of Planned Behavior incorporates environmental concern and knowledge as antecedents of attitude and demonstrates the mediating role of lifestyle orientation between knowledge and purchasing behavior (Moser, 2015). In digital and AI-mediated contexts, sustainable consumption behavior (SCB) has additional determining factors. Previous research has found that AI-based digital platforms create an information framework that reduces the search costs for sustainable alternatives, thereby increasing the likelihood of purchasing eco-friendly products (Wongloet et al., 2023). They identified culture, social identity, and gender as moderators of the relationship between attitudes and behavior in eco-friendly purchasing; these findings are highly relevant to the identity formation of sustainability-conscious Generation Z. The impact of AI personalization on sustainable consumption, which noted a 34% increase in the selection of sustainable products when AI recommendations align with environmental values—a finding that serves as a theoretical foundation for examining AI adoption as a predictor of SCB (Jiménez-Barreto et al., 2022).

## 4. Indicator Development and Measurement Framework

### *4.1 AI Adoption Indicators*

The following AI adoption indicators are synthesized from Dwivedi and Venkatesh and adapted for the context of consumer AI (e-commerce personalization, virtual assistants, and recommendation systems) (Dwivedi et al., 2019) (Venkatesh et al., 2012). A specific dimension regarding the application of AI for sustainability was added to capture consumers' understanding and use of AI tools in actual resource-saving behaviors—including energy monitoring, water conservation, and carbon footprint tracking—a dimension that was underrepresented in previous TAM/UTAUT instruments but is increasingly relevant in AI-based smart home applications and eco-friendly behaviors. The statement items were formulated using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

**Table 1. Dimension codes and AI Adoption Indicators based on the source document**

| Code | Dimension | Indicator Item | Source |
|---|---|---|---|
| AI1 | Perceived Usefulness | Using AI-based applications helps me find sustainable products more efficiently. | (Davis, 1989)(Jiménez-Barreto et al., 2022) |
| AI2 | Perceived Usefulness | AI recommendations improve the quality of my purchasing decisions. | (Davis, 1989) (Garrett et al., 2023) |
| AI3 | Perceived Usefulness | AI tools save me time when searching for environmentally friendly products. | (Venkatesh et al., 2003) |
| AI4 | Perceived Ease of Use | Interacting with AI-powered platforms is simple and intuitive for me. | (Davis, 1989) (Marangunić & Granić, 2015) |
| AI5 | Perceived Ease of Use | I can quickly learn how to use new AI features without external assistance. | (Wang & Chuang, 2024) |
| AI6 | Behavioral Intention | I intend to continue using AI-based services in my future consumption activities. | (Venkatesh et al., 2012) |
| AI7 | Behavioral Intention | I plan to increase my use of AI tools for making purchasing decisions. | (Benbya et al., 2021) |
| AI8 | Actual Use | I regularly use AI recommendation systems when shopping online. | (Pillai et al., 2020) |
| AI9 | Actual Use | AI assistants are part of my daily digital consumption routine. | (Randers et al., 2021) |
| AI10 | Trust in AI | I trust the recommendations provided by AI systems I use. | (Longoni et al., 2019) |
| AI11 | Trust in AI | AI systems I interact with make transparent and explainable suggestions. | (Puntoni et al., 2021) |
| AI12 | Hedonic Motivation | Using AI-powered apps is enjoyable and engaging for me. | (Baptista & Oliveira, 2015) (Venkatesh et al., 2012) |
| AI13 | AI for Energy & Water Saving | I use AI-powered smart home or energy management applications to monitor and reduce my electricity and water consumption. | (Salvi et al., 2023) |
| AI14 | AI for Carbon Footprint Awareness | AI tools help me calculate and understand the carbon footprint of my daily consumption choices (e.g., food, transportation, fashion). | (Dwivedi et al., 2019)(Wongloet et al., 2023) |
| AI15 | AI for Sustainable Resource Management | AI-based applications I use provide actionable suggestions to help me reduce waste, save water, and optimize resource use in my daily life. | (Yuan et al., 2021) (Joiner et al., 2023) |

### *4.2 Technostress Indicators*

The technostress indicators were adapted from the Technostress Creator Scale (TCS) developed by Tarafdar (Tarafdar et al., 2015) and subsequently validated in subsequent studies (Ragu-

Nathan et al., 2008). To ensure relevance to the context of this study, all items were modified from their original work-related context to reflect consumers' interactions with artificial intelligence technology in daily life. Specifically, references to workplace technology, work-related tasks, and the organizational environment were reworded to capture AI-related experiences in the context of personal consumption and everyday use, while retaining the conceptual meaning of the original construct.

**Table 2. Dimension codes and Technostress Indicators based on source documents**

| Code | Dimension | Indicator Item | Source |
|---|---|---|---|
| TS1 | Techno-overload | I feel overwhelmed by the amount of information generated by AI systems I use. | (Brand, n.d.) (Ayyagari et al., 2011) |
| TS2 | Techno-overload | AI-driven notifications and updates make me feel pressured to act immediately. | (Ragu-Nathan et al., 2008) |
| TS3 | Techno-overload | Using multiple AI platforms simultaneously increases my mental workload. | (Shu et al., 2011) |
| TS4 | Techno-invasion | AI applications make me feel that I must remain available and responsive at all times. | (Tarafdar et al., 2007) |
| TS5 | Techno-invasion | Technology disrupts my personal time and space more than I would like. | (Throuvala et al., 2019) |
| TS6 | Techno-invasion | AI-enabled connectivity invades my sense of privacy and personal boundaries. | (Ragu-Nathan et al., 2008) |
| TS7 | Techno-complexity | I find AI-powered platforms difficult to understand and use effectively. | (Fuglseth & Sørebø, 2014) |
| TS8 | Techno-complexity | Frequent updates and changes to AI features make me anxious about keeping up. | (Salanova et al., 2013) |
| TS9 | Techno-complexity | I spend too much time trying to figure out how AI systems work. | (Shu et al., 2011) |
| TS10 | Techno-insecurity | I worry that AI will make my existing skills and knowledge obsolete. | (Tarafdar et al., 2015) |
| TS11 | Techno-insecurity | I feel threatened by people who know more about AI than I do. | (Ragu-Nathan et al., 2008) |
| TS12 | Techno-insecurity | I am afraid that my inability to keep up with AI developments will put me at a disadvantage. | (Brand, n.d.) |
| TS13 | Techno-uncertainty | The rapidly changing nature of AI technology makes me uncertain about the future. | (Tarafdar et al., 2007) |
| TS14 | Techno-uncertainty | I am unsure how to adapt when AI platforms change their algorithms or interface. | (Ayyagari et al., 2011) |
| TS15 | Techno-uncertainty | The unpredictability of AI-driven recommendations causes me stress. | (Throuvala et al., 2019) |

### *4.3 Sustainable Consumption Behavior Indicators*

The Sustainable Consumption Behavior (SCB) indicator was synthesized from well-established scales in the sustainable consumption literature and subsequently adapted for this study. This adaptation process involved revising the wording of the indicator items to reflect

consumption decisions influenced by digital technologies and AI-based services, which have become an integral part of Generation Z consumers' daily lives. Throughout this process, special attention was given to preserving the conceptual meaning of the original measurement instrument while enhancing its relevance to the new, technology-driven consumption context.

**Table 3. Dimension codes and indicators for Sustainable Consumption Behavior based on document sources**

| Code | Dimension | Indicator Item | Source |
|---|---|---|---|
| SCB1 | Green Purchasing | I actively use AI recommendations to identify and purchase eco-friendly products. | (Jaiswal & Kant, 2018) |
| SCB2 | Green Purchasing | I prefer to buy products recommended by AI that have low environmental impact. | (Moser, 2015)(Follows & Jobber, 2000) |
| SCB4 | Ethical Consumption | I choose products suggested by AI that align with fair-trade and ethical standards. | (Sreen et al., 2018) |
| SCB5 | Sharing Economy | I participate in sharing economy platforms (e.g., rental, resale) facilitated by AI matching systems. | (Bocken et al., 2014) |
| SCB6 | Waste Minimization | I use AI-based apps to track and reduce waste from my consumption activities. | (Maniatis, 2016) |
| SCB7 | Waste Minimization | AI recommendations have helped me shift toward a more minimalist consumption lifestyle. | (Nguyen et al., 2025) |

### *4.4 Summary of Indicator Framework*

Table 4 presents a comprehensive summary of the measurement framework used in this study. Specifically, the table outlines the constructs under investigation, the number of indicators used to operationalize each construct, the underlying theoretical basis, and the recommended Likert scale. This table also illustrates how established measurement scales have been adapted to the context of AI-mediated consumption and sustainable behavior among Generation Z, while maintaining conceptual consistency with the prior literature.

**Table 4. Summary of Dimensions and Indicators for AI Adoption, Technostress, and Sustainable Consumption Behavior**

| Construct | Dimensions | # Indicators | Theoretical Basis | Scale |
|---|---|---|---|---|
| AI Adoption | Perceived Usefulness, Ease of Use, Behavioral Intention, Actual Use, Trust, Hedonic Motivation, AI for Sustainability Implementation | 15 (AI1–AI15) | TAM<br>UTAUT | 5-point Likert |
| Technostress | Techno-overload, Techno-invasion, Techno-complexity, Techno-insecurity, Techno-uncertainty | 15 (TS1–TS15) | Technostress Framework<br>COR Theory | 5-point Likert |
| Sustainable Consumption Behavior | Green Purchasing, Ethical Consumption, Sharing Economy, Waste Minimization | 7 (SCB1–SCB7) | TPB | 5-point Likert |
| Total | 12 sub-dimensions | 37 indicators | 5 core theoretical frameworks | 5-point Likert |

### *4.5 Conceptual Model and Hypothesized Relationships*

Building on the three theoretical pillars synthesized above, Figure 1 integrates AI Adoption, Technostress, and Sustainable Consumption Behavior (SCB) into a single conceptual model, bounded by Indonesian Generation Z as the target population. The model formalizes the dual pathway implied throughout this review: AI adoption is expected to increase technostress through the mechanisms described in Section 3.2 (P1), while technostress, through the resource-depletion logic of Conservation of Resources (COR) Theory, is expected to reduce engagement in the deliberative, multi-criteria evaluation that sustainable consumption requires (P2). At the same time, AI adoption is expected to exert a direct, positive effect on SCB through mechanisms such as AI-curated sustainability information and reduced search costs for eco-friendly alternatives, net of its indirect effect through technostress (P3). Together, P1–P3 specify a mediation structure in which technostress partially transmits the effect of AI adoption on SCB, providing explicit, testable propositions for the subsequent quantitative validation phase of this research.

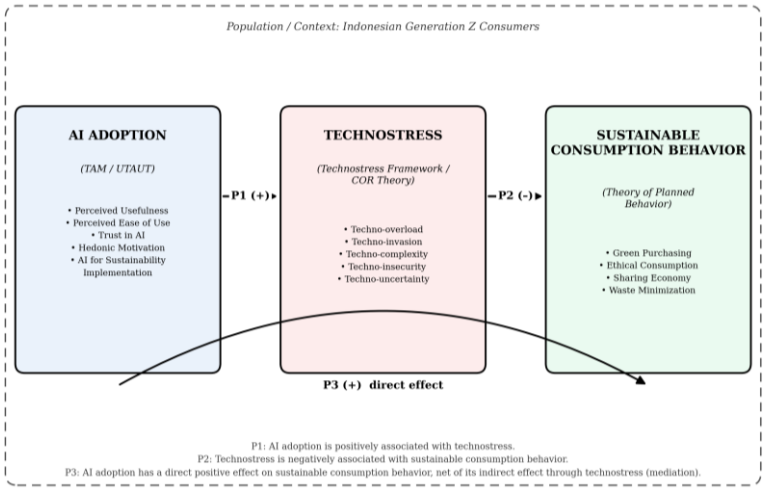



**Figure 1. Conceptual model of AI adoption, technostress, and sustainable consumption behavior among Indonesian Generation Z consumers, with hypothesized propositions P1–P3.**

## 5. Conclusion

This systematic literature review has synthesized research spanning the fields of technology acceptance, technostress, and sustainable consumption behavior to develop a measurement framework with a strong theoretical and empirical foundation, consisting of 37 validated indicators across three main constructs. This integrated model based on TAM/UTAUT, the Technostress Framework, Resource Conservation Theory, and Theory of Planned Behavior provides a solid conceptual and instrumental foundation for future quantitative research on how AI adoption and technostress jointly shape sustainable consumption behavior among Generation Z.

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