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AI Stimuli and Responsible Consumer Choices: Understanding the Pathways to Sustainability

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Abstract

This study examines how AI stimuli promote sustainable consumption using the stimulus-organization-response (SOR) model and Theory of Planned Behavior (TPB). Surveying 400 Gen Z consumers in Egypt, it explores the mediating roles of passion, usability, perceived interactivity, and relative advantage. Structural Equation Modeling (SEM) reveals that both emotional (Passion) and functional (Usability) AI features significantly influence eco-conscious behaviors through customer engagement and intelligent experiences. By integrating emotional and functional AI dimensions within a sustainability framework, the research offers theoretical insights and practical strategies for businesses to enhance user engagement and responsible consumption through interactive, personalized AI systems. Limitations include the demographic focus and reliance on self-reported data, suggesting future research adopt longitudinal and cross-cultural approaches to further explore AI's role in global sustainability.
Keywords: Artificial Intelligence Stimuli, Sustainable Consumption Behavior, Customer Engagement, Smart Customer Experience, Generation Z, PassionandUsability Factors, Perceived Interactivity, Relative Advantage, Structural Equation Modeling, Sustainability Frameworks.

Introduction

The evolution of artificial intelligence (AI) technologies has redefined consumer interactions with the digital environment, fostering innovation across sectors such as marketing and consumer experience. AI's ability to deliver intelligent, personalized, and efficient experiences has become a cornerstone of modern consumer engagement, influencing preferences, purchasing decisions, and loyalty (Behera, Nanda, &Derbali, 2024; Mariani et al., 2022). These AI-driven interactions are increasingly significant in creating "smart customer experiences," characterized by dynamic interactivity and tailored personalization. At the same time, global environmental and social challenges have emphasized the need for sustainable consumption behaviors—practices that consider the long-term social, economic, and environmental impacts of consumer decisions (Garcelon et al., 2020). The convergence of AI technologies with sustainability goals presents a unique opportunity to understand how AI stimuli can influence responsible consumption behaviors.

Sustainable consumption behaviors represent consumer decisions guided by principles such as minimizing resource use, prioritizing ethical production, and embracing environmentally friendly practices (Matharu et al., 2024). These behaviors align with global objectives, such as the United Nations' Sustainable Development Goal 12, which advocates for responsible consumption and production. However, leveraging AI to drive sustainable consumption requires deeper insights into how AI stimuli—encompassing both emotional aspects like passion and functional attributes like usability—can mediate consumer behaviors. Importantly, customer engagement and smart customer experiences emerge as critical dimensions in this context, as they bridge the gap between technological stimuli and behavioral outcomes (Ameen et al., 2020).

This study is grounded in two complementary theories: the Stimulus-Organism-Response (SOR) model and the Theory of Planned Behavior (TPB). The SOR model, first introduced by Mehrabian and Russell (1974), posits that external stimuli (S) affect the internal state of an organism (O), which subsequently drives behavioral responses (R). In this context, AI stimuli act as the external triggers influencing customer engagement (the organism), which then leads to sustainable consumption behaviors (the response). This framework highlights the importance of perceived interactivity, personalization, and usability in fostering meaningful consumer experiences that promote sustainability.

The Theory of Planned Behavior (Arkes et al., 1991) complements the SOR model by emphasizing the role of behavioral intentions and perceived behavioral control. According to TPB, individuals' behaviors are influenced by their attitudes, subjective norms, and perceived control over the behavior. AI technologies can enhance these aspects by providing consumers with the tools and confidence to make sustainable choices. For instance, smart customer experiences driven by AI can strengthen consumers' intention to adopt sustainable practices by simplifying decision-making processes and emphasizing eco-conscious values. The integration of these theories offers a robust framework for exploring how AI stimuli shape sustainable consumption through customer engagement and smart customer experiences.

Despite increasing attention to AI's role in consumer behavior, the mechanisms linking AI stimuli to sustainable consumption behaviors remain underexplored. Previous research has highlighted indirect pathways, such as using customer stickiness and perceived emotional value to influence sustainable consumption behaviors (Cao & Liu, 2023). Studies have also demonstrated the direct impact of perceived interactivity and personalization in enhancing value co-creation and customer experiences (Gao et al., 2023). However, there is limited understanding of how AI stimuli contribute to sustainable consumption through the mediating roles of customer engagement and smart customer experiences. Specifically, the interplay between emotional (e.g., passion) and functional (e.g., usability) AI stimuli and their capacity to foster eco-conscious consumption through dynamic consumer interactions remains a critical gap. Therefore, this study would like to examine:

RQ1. How does passion as an emotional AI stimulus influence customer engagement and perceived interactivity in the context of sustainable consumption?

RQ2. What role does usability as a functional AI stimulus play in shaping smart customer experiences and sustainable consumption behavior?

RQ3. How do constructs like perceived interactivity and relative advantage mediate the impact of AI stimuli on sustainable consumption?

RQ4. To what extent does customer engagement mediate the relationship between AI stimuli (passion, usability) and sustainable consumption?

RQ5. How can AI-driven smart customer experiences connect online consumer engagement with offline sustainable behaviors?

While frameworks like the Stimulus-Organism-Response (SOR) theory and Theory of Planned Behavior (TPB) suggest theoretical pathways for understanding behavior, their application in linking AI stimuli with sustainable consumption remains insufficient. Existing studies have primarily examined the direct effects of AI on consumer behaviors without delving into the nuanced roles of customer engagement and smart customer experiences as mediators. Furthermore, the capacity of AI-driven interactivity and personalization to bridge online and offline sustainability behaviors remains poorly understood. This study aims to fill this gap by integrating emotional and functional dimensions of AI stimuli into a comprehensive framework, advancing the understanding of how AI technologies can foster responsible consumption behaviors. By focusing on the roles of customer engagement and smart customer experiences, this research contributes to both theoretical advancements and practical strategies for aligning AI technologies with global sustainability goals. It provides actionable insights for businesses and policymakers seeking to leverage AI for promoting eco-conscious consumer practices.

AI Technology Experience

AI technologies have revolutionized the online purchasing experience by introducing advanced features such as intelligent recognition, personalized recommendations, and virtual customer support. These developments provide consumers with highly accurate, insightful, and interactive experiences, enhancing convenience and satisfaction (Li, 2021). (A) Accuracy Experience: AI uses vast datasets to deliver precise solutions, enabling consumers to quickly find products using text, voice, or image searches. Platforms like Taobao and Jingdong exemplify this capability, offering accurate product recommendations that streamline the search process. (B) Insight Experience: Machine learning enables AI to analyze user preferences and tailor website content accordingly. This personalization, reflected in customized product suggestions and demand forecasting, creates an insightful shopping experience that meets individual consumer needs. (C) Interactive Experience: AI-powered virtual assistants, such as Echo and Tmall Genie, replace human customer service with dynamic, natural language interactions. These tools empower consumers to make informed decisions through seamless and engaging dialogues. By integrating accuracy, insight, and interactivity, AI technologies transform digital purchasing, fostering deeper consumer engagement and paving the way for smarter, more sustainable customer experiences.

The Stimulus-Organism-Response (SOR) Model

The stimulus-organization-response (SOR) model, proposed by Foxall (1974), explains how external stimuli (S), such as environmental cues, influence internal cognitive and emotional states (O), which ultimately drive behavioral responses (R). Initially applied to general consumer behavior, the model has since been extended to various domains, including online shopping. For example, Taylor and Strutton (2010) utilized the SOR framework to explore how consumer preferences and cognitive states affect purchasing behaviors, while Eroglu et al. (2001) adapted it for online shopping platforms, highlighting its relevance in digital environments.

In the context of AI technologies, the SOR model provides a structured approach to studying how AI-driven stimuli influence consumer behavior. Stimuli such as perceived interactivity, personalization, and social presence impact consumers' emotional and cognitive responses, enhancing their engagement and decision-making processes (Gao et al., 2023). These stimuli are central to understanding the role of AI in shaping consumer experiences, particularly through factors like perceived usefulness, perceived information quality, and social contact.

Empirical studies have demonstrated the efficacy of the SOR model in the AI domain. Yin and Qiu (2022) investigated AI marketing on online platforms, finding that AI-enhanced tools improve consumers' perceived utilitarian and hedonic values, boosting their perceived value and purchasing intentions. This highlights the importance of investing in AI technologies such as intelligent search and personalized recommendations to enhance shopping experiences and drive precision marketing. However, additional research is needed to explore moderating variables and long-term impacts to comprehensively understand AI's influence on consumer behavior.

The potential of AI marketing technologies extends beyond improving purchasing experiences to addressing broader sustainability challenges. Local sustainability initiatives, driven by technological, social, and economic innovations, illustrate how AI can support global efforts to tackle issues like health, mobility, and biodiversity loss (Winarto&Wisesa, 2024; Gordon et al., 2016). By incorporating sustainability into AI applications, businesses can align consumer experiences with global environmental goals.

Finally, the SOR framework provides a robust theoretical basis for analyzing the impacts of AI stimuli on consumer behavior. By integrating dimensions such as interactivity, personalization, and social presence, AI technologies can enhance both individual purchasing experiences and broader sustainability outcomes. Future research should further explore the interplay of AI-driven stimuli with moderating variables to optimize their effectiveness in fostering responsible consumer behaviors.

Various Facets of Sustainable Consumption

Sustainable consumption has become a vital response to the pressing environmental, social, and economic challenges of contemporary consumption patterns. While consumption is fundamental for fulfilling basic human needs and improving quality of life, unsustainable practices have led to resource depletion, ecosystem degradation, and increased pollution. These challenges demand a transition toward sustainable consumption models that balance individual needs with broader societal and environmental goals (Brzustewicz& Singh, 2021).

Various definitions of sustainable consumption highlight its multi-dimensional nature. One of the most cited is from the Norwegian Ministry of Environment at the 1994 Oslo Roundtable, defining it as "the use of goods and services that respond to basic needs and bring a better quality of life, while minimizing the use of natural resources, toxic materials, and emissions of waste and pollutants over the life cycle, so as not to jeopardize the needs of future generations." Similarly, the United Nations Environment Programme (UNEP) describes sustainable consumption as a holistic approach that minimizes environmental impacts while promoting societal well-being. These principles are reflected in the UN's 2030 Agenda for Sustainable Development, particularly in Goal 12, which emphasizes responsible consumption and production as pathways to a low-carbon and resource-efficient economy (Brzustewicz& Singh, 2021).

Sustainable consumption incorporates themes such as balancing needs and wants, enhancing efficiency, managing waste, and adopting a life cycle perspective. At a macro level, this requires radical changes in resource usage, waste management, and pollution control. Businesses must embrace sustainability throughout the product life cycle using approaches like "cradle-to-cradle" and "cradle-to-grave" frameworks. These ensure that sustainability considerations are embedded in design, production, and disposal processes, creating a foundation for responsible consumption (Brzustewicz& Singh, 2021).

Incorporating artificial intelligence (AI) into sustainable consumption frameworks offers new pathways to influence consumer behavior. Studies have demonstrated that emotional and functional factors, such as passion and usability, drive consumer engagement and interactivity, which are critical for promoting sustainability.

- **Passion** positively affects customer engagement **(H1)**, perceived interactivity **(H2)**, and relative advantage **(H3)**.
- Usability fosters customer engagement **(H4)**, perceived interactivity **(H5)**, and relative advantage **(H6)**.
- Moreover, constructs like perceived interactivity **(H7)**, relative advantage **(H8)**, and customer engagement **(H9)** have been shown to positively impact **sustainable consumption behaviors**. These insights highlight the potential of AI-driven interventions to align consumer practices with sustainability objectives.

The Mediating Effect of Customer Engagement

Customer engagement (CE) is a dynamic, multidimensional psychological state arising from interactive and co-creative experiences with a brand or service (Brodie et al., 2011). It involves cognitive, emotional, and behavioral dimensions, operating within a network were concepts like loyalty and involvement act as antecedents and consequences.

The Stimulus-Organism-Response (SOR) theory explains how external stimuli, such as AI-driven interactions, trigger organismic responses like engagement, leading to behavioral outcomes (Mehrabian & Russell, 1974). AI stimuli enable firms to manage real-time customer interactions efficiently, fostering engagement and customer stickiness, which indirectly promote sustainable behaviors (Perez-Vega et al., 2021; Cao & Liu, 2024).

Studies show customer engagement's mediating role in linking AI stimuli to sustainable consumption. Cao and Liu (2023) identify how engagement connects online green habits with offline sustainability. Pérez et al. (2020) emphasize CE's importance in understanding sustainable behaviors, while Chen et al. (2022) notes context-dependent complexities, such as AI's varying effects on trust and engagement.

Artificial Intelligence Technology Stimuli and Cognitive Smart Customer Experience

AI technology stimuli significantly influence the degree of pleasure and usefulness customers experience while interacting with AI-driven tools, such as intelligent customer service robots, augmented reality (AR) technology, and digital assistants. These stimuli can be categorized into **Passion(emotional)** and **usability (functional)** dimensions, represented by passion and usability, respectively. Both dimensions play an essential role in enhancing cognitive smart customer experiences and promoting sustainable consumption behaviors.

Passion, as a hedonic stimulus, represents the positive emotional connection users develop toward AI technologies. Intelligent voice robots exemplify this by fostering enjoyment, interaction, and socialization, enabling users to experience passion exclusively through AI (Gao et al., 2022). Such emotional engagement enhances customer experiences and satisfaction, reinforcing loyalty and promoting optimal experiences. For example, AI systems that provide hedonic stimuli positively influence perceived interactivity (**H11**), customer engagement (**H12**), and relative advantage (**H13**), ultimately fostering sustainable consumption behaviors.

Usability, as a utilitarian stimulus, refers to the ease with which customers can understand, control, and use AI technologies. High usability ensures personalized interactions, enabling AI to accurately assess and respond to customer needs efficiently (Zhang et al., 2014; Gao & Bai, 2014). In social commerce, usability contributes to interactivity, availability, and informativeness, creating a seamless customer experience. Usability stimuli influence perceived interactivity (**H14**) and customer engagement (**H15**), linking functional stimuli to sustainable consumption behavior.

AI stimuli extend beyond individual experiences to broader behavioral impacts. For instance, AI-driven platforms like **Ant Forest** integrate virtual and real-world elements to promote low-carbon living, encouraging users to adopt energy-saving and emission-reducing habits (Cao & Liu, 2023). These platforms gamify sustainable actions, transforming users into advocates for environmental causes and fostering self-fulfillment. Similarly, AI systems use customer insights to create personalized, automated responses that increase engagement and profitability while supporting sustainable practices (Perez-Vega et al., 2021).

In conclusion, artificial intelligence technology stimuli, through their hedonic and utilitarian dimensions, play a crucial role in enhancing cognitive smart customer experiences. Passion drives emotional connections, while usability ensures functional efficiency, both contributing to sustainable consumption behaviors. Mediating factors such as perceived interactivity, customer engagement, and relative advantage underscore the pathways linking AI stimuli to positive outcomes, making AI a powerful tool for promoting sustainability.

Theoretical Model

The proposed theoretical model integrates the stimulus-organization-response (SOR) framework with insights into artificial intelligence (AI) stimuli to understand their influence on customer engagement, smart customer experience, and sustainable consumption behaviors. The model captures how Passion and usability stimuli, mediated by cognitive and emotional processes, shape consumer outcomes.

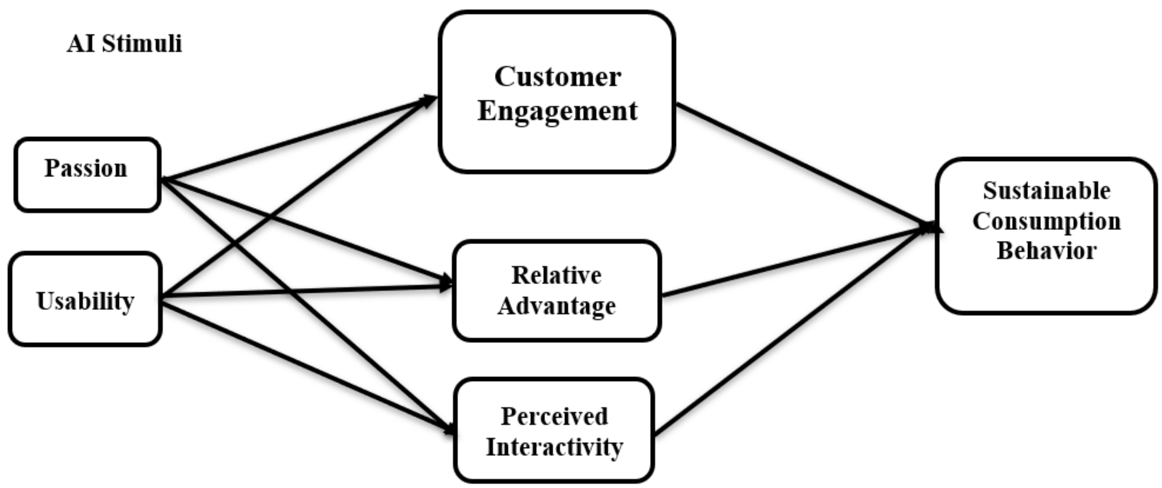

Figure 1 Theoretical Model

Research Methodology

This study employs a **quantitative research approach** to empirically test the proposed hypotheses related to artificial intelligence (AI) technology stimuli, customer engagement, and sustainable consumption behavior. The methodology encompasses questionnaire design, sampling strategy, data collection, and statistical analysis.

Questionnaire Design

The data were gathered through a structured questionnaire comprising five sections:

1. **Demographic Information**: Included age, gender, occupation, education, and income.
2. **Theoretical Variables**: Corresponded to the research constructs: Passion, Usability, Emotional Value, Social Value, Customer Engagement, Relative Advantage, Perceived Interactivity, and Sustainable Consumption Behavior (SCB).

All research variables, except for demographic information, were assessed using a **7-point Likert Scale**, ranging from 1 (completely disagree) to 7 (completely agree). Items for the variables were drawn from established scales to ensure reliability and validity:

- **Relative Advantage**: Measured using six items adapted from Lu et al. (2019).
- **Perceived Interactivity**: Measured using four items based on Roy et al. (2019).
- **Sustainable Consumption Behavior**: Assessed using the 7-point Likert scale, as outlined in Table 1 (Measurement Scale).

A pre-survey of 50 questionnaires yielded 42 valid responses, confirming scale validity with **Cronbach's alpha values exceeding 0.70**, as recommended by Kaihatu (2020).

Sampling and Population

According to the research objectives, the research population is heterogeneous in terms of gender, age, and conclusive in nature. Therefore, probability sampling would have been the most favorable option, as it permits the researcher to make statistical assumptions about the whole target population. However, this option could not be appropriate since it entails the possession of a sampling frame over the entire population, which the researcher is not able to get (Malhotra & Birks, 2007). Therefore, the researcher chose the second possible technique: non-probability quota sampling, which is also known as deliberate sampling. This technique was used to select **Generation Z** in Egypt. Regarding sample size, In theory, a large sample size ensures both a higher accuracy of results and a better balance between the proportions in the sample and the proportions in the overall sampling frame. The sample size should be large enough as the researcher aims to analyze quantitative data using statistical methods (Malhotra & Birks, 2007).

The researcher used the following equation to estimate the sample size

n= [(Np (1-p) / ((N-1) d2/z2)) +p (1-p)],

where: N: Population size D: The acceptable error ratio for the estimation is 0.05 Z: The standard score for the confidence level = 95% (1.96) P: The proportion of a population with a particular characteristic is 0.5
So, the calculated sample size from the previous equation is N= (31620000*0.5*0.5)/ ((31619999*(0.05*2)/ (1.96*2) + (0.5*0.5)) = 384.155

The study targeted **Generation Z** in Egypt, defined as individuals aged 18 to 26, representing approximately 37% of the Egyptian population (40 million people, per the 2024 Census). The sample size was calculated using **Slovin's Formula** with a 5% margin of error, resulting in a required sample of **400 respondents**.

Data Collection

Data were collected through an **online survey** administered via **Qualtrics XM**. The questionnaire was designed to explore Gen Z consumers' experiences with eco-conscious practices, including their passion and usability, sustainability concerns, and consumption behaviors related to eco-conscious practices.

Generation Z Characteristics

Generation Z is characterized by its affinity for innovation and demand for seamless, technology-enabled shopping experiences. Members of this cohort are known for making quick, informed online shopping decisions, often relying on product reviews, visibility, and competitive pricing (Lauring&Steenburg, 2019; Priporas et al., 2017). Unlike previous generations, Gen Z exhibits less brand loyalty and is generally non-impulsive in their purchasing behavior (Eom&Seock, 2017; Thomas et al., 2018). While cohort studies provide a broad understanding, individual-level variations within Gen Z warrant closer examination (Okros, 2020).

Data Analysis

The collected data were analyzed using **SmartPLS v.4**, following a structured process:

1. **Preliminary Tests**: Assessed the normality, reliability, and validity of the data.
2. **Confirmatory Factor Analysis (CFA)**: Conducted within a **Structural Equation Modeling (SEM)** framework to validate the model fit.
3. **Path Coefficient Analysis**: Performed to test the relationships outlined in the theoretical model, including multi-group analysis to explore variations within the dataset.

Measurements of Variables

The study employed established scales to measure the constructs:

- **Passion and Usability**: Representing AI technology stimuli, assessed their influence on customer engagement and SCB.
- **Relative Advantage**: Measured with six items from Lu et al. (2019).
- **Perceived Interactivity**: Evaluated using four items based on Roy et al. (2019).
- **Sustainable Consumption Behavior**: Assessed on a 7-point Likert scale, aligning with the constructs in Table 1.

Table 1 Measurement scale

Constructs	Scale Items	Source
Passion	I am willing to use intelligent customer service robots because I am passionate about it. I use intelligent customer service robots because I like it. My passion for this intelligent customer service robot makes me want to use it. I like using intelligent customer service robots because I can use my experience to help other people. I really like helping other users with their questions when they are using intelligent customer service robots. I feel good when I can help answer questions that other users have with intelligent customer service robots.	Herrando et al. (2019) and Baldus et al. (2015)
Usability	1- Everything is easy to understand when using intelligent customer service robots. 2- Intelligent customer service robots are simple to use, even when using them for the first time. 3- It's easy for me to get the information I need when using an intelligent customer service robot. 4- When using an intelligent customer service robot, I feel	**Flavian et al. (2006)**

	that I am in control of what I can do. 5- When using intelligent customer service robots, I can get fast service.	
Customer Engagement	1- I feel like I can be myself when using intelligent customer service robots. 2- The things I did with the intelligent customer service robots are in line with what I really wanted to do. 3- Using intelligent customer service robots has become a part of my daily consumption. 4- I think I have a strong emotional connection with intelligent customer service robots	**Hsieh and Chang (2016) and Nambisan and Baron (2009).**
Relative advantage	1- Intelligent customer service robots offer consistent service and results over time. 2- Intelligent customer service robots provide more accurate service than human customer service. 3- Information provided by intelligent customer service robots is more accurate with fewer human errors in services. 4- Intelligent customer service robots are more dependable than human customer service. 5- Service provided by intelligent customer service robots is more predictable than human customer service. 6- I am able to avoid inefficient personal contacts if I use intelligent customer service robots.	**(Vallerand et al., 2003; Lavigne et al., 2012; Carpentier et al., 2012).**
Perceived interactivity	1- Intelligent customer service robots have the ability to respond to my specific needs quickly and efficiently. 2- When using an intelligent customer service robot, I can choose which stores I want. 3- When using an intelligent customer service robot, I have some control over the content of the interaction. 4- When using an intelligent customer service robot, I can control the frequency of interactions.	**(Zhang et al., 2014; Gao and Bai, 2014).**
Sustainable Consumption Behavior (SCB)	1- I perform daily activities to care for and preserve the environment. 2- I would like to make changes in my lifestyle in search of more responsible consumption. 3- I am satisfied with my responsible consumption behaviors. 4- I purchase and use environmentally friendly products.	**Muhammad et al., 2020 & Huang et al., 2023**

Statistical Analysis and Results

The statistical analysis for this study involved both descriptive and inferential techniques. Python statistical libraries, including NumPy and Pandas, were employed to manage and analyze large datasets efficiently. These libraries provided data structures and functions necessary for comprehensive statistical modeling. In addition to descriptive statistics, inferential analyses were conducted using Smart-PLS 4 software, including validity tests, confirmatory factor analysis (CFA), reliability assessment, and Structural Equation Modeling (SEM) for hypothesis testing.

Descriptive Data and Measurements

Descriptive statistics for the research variables are presented in Table 1. The results indicate that the mean values for all dimensions exceed 4, suggesting that respondents generally agree with the items across all constructs. Furthermore, the variance inflation factor (VIF) was assessed to examine multi-collinearity issues. According to Mandal (2017), VIF values should be 3.3 or less to ensure that multi-collinearity does not distort the analysis. The

VIF values for all variables in this study ranged between 1.010 and 3.323, confirming that multi-collinearity is not a concern (Table 2).

Table 2 Descriptive statistics of constructs

Items	Mean	Std. deviation	VIF
PA1	5.795	1.084	1.947
PA2	5.708	1.010	2.302
PA3	5.562	1.229	1.897
PA4	5.720	1.127	2.129
PA5	5.568	1.193	1.546
PA6	5.878	1.114	2.302
US1	5.540	1.165	2.102
US2	5.632	1.084	2.139
US3	5.812	1.096	1.499
US4	5.370	1.693	3.323
US5	5.528	1.533	3.272
CE1	5.980	1.023	1.714
CE2	5.525	1.197	1.482
CE3	5.585	1.162	1.330
CE4	5.735	1.168	1.691
RA1	5.368	1.410	1.605
RA2	5.995	1.067	1.396
RA3	5.328	1.300	1.425
RA4	5.575	1.126	2.142
RA5	5.675	1.115	2.067
RA6	5.490	1.249	1.816
PI1	5.812	1.010	1.426
PI2	5.800	1.117	2.280
PI3	5.540	1.205	2.336
PI4	5.645	1.176	2.046
SCB1	5.802	1.015	1.005
SCB2	5.652	1.393	1.351
SCB3	6.065	1.172	3.220
SCB4	6.035	1.191	3.186

Exploratory Factor Analysis (EFA)

To identify the main factors within the dataset, XLSTAT software was used to perform an Exploratory Factor Analysis (EFA). Principal Component Analysis (PCA) was employed to extract factors, and factor loadings were calculated for each of the 29 variables. The suitability of the data for factor analysis was confirmed through Bartlett's Test of Sphericity, which produced a high chi-square value of 7244.444 with df = 406 and a p-value of 0.0. These results indicate that the correlation matrix significantly differs from an identity matrix, making the dataset appropriate for factor analysis.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was computed for the five latent variables. The KMO values for each variable were as follows: Passion (0.879), Relative Advantage (0.879), Perceived Interactivity (0.802), Customer Engagement (0.717), Usability (0.692), and Sustainable Consumption Behavior (0.630). The overall KMO score of 0.935 signifies "Marvelous" sampling adequacy, further confirming that the data is highly suitable for factor analysis across all 29 variables.

Confirmatory Factor Analysis (CFA)

Following the EFA, a Confirmatory Factor Analysis (CFA) was conducted using Smart-PLS software to validate the measurement model. All 29 items were included in the CFA to assess their alignment with the theoretical constructs. The results of the first-order CFA indicated appropriate factor loadings for all variables, confirming their reliability and suitability for further data analysis. The cross-loading criterion was met, as detailed in Table 3.

Table 3 Cross-loading of the variables

	Customer Engagement	**Passion**	**Perceived Interactivity**	**Relative Advantage**	**SCB**	**Usability**
CE1	0.790	0.656	0.607	0.699	0.667	0.649
CE2	0.755	0.603	0.588	0.529	0.601	0.601
CE3	0.793	0.685	0.690	0.710	0.706	0.638
CE4	0.844	0.690	0.630	0.680	0.683	0.616
PA1	0.622	0.760	0.605	0.541	0.579	0.612
PA2	0.646	0.771	0.817	0.769	0.677	0.552
PA3	0.719	0.785	0.635	0.659	0.638	0.643
PA4	0.579	0.792	0.518	0.552	0.580	0.671
PA5	0.644	0.814	0.699	0.665	0.656	0.611
PA6	0.639	0.824	0.828	0.671	0.640	0.617
PI1	0.630	0.670	0.793	0.606	0.612	0.804
PI2	0.627	0.806	0.826	0.663	0.626	0.608
PI3	0.646	0.771	0.817	0.769	0.677	0.552
PI4	0.517	0.437	0.811	0.410	0.436	0.549
RA1	0.710	0.669	0.635	0.771	0.782	0.616
RA2	0.611	0.666	0.703	0.773	0.639	0.527
RA3	0.426	0.464	0.444	0.782	0.404	0.443
RA4	0.676	0.669	0.637	0.824	0.832	0.565
RA5	0.607	0.632	0.632	0.776	0.631	0.530
RA6	0.660	0.658	0.608	0.735	0.664	0.650
SCB1	0.663	0.704	0.660	0.726	0.813	0.661
SCB2	0.655	0.645	0.617	0.803	0.827	0.548
SCB3	0.682	0.627	0.601	0.732	0.775	0.593
SCB4	0.608	0.549	0.534	0.466	0.783	0.563
US1	0.495	0.511	0.466	0.454	0.489	0.708
US2	0.627	0.680	0.664	0.632	0.613	0.770
US3	0.630	0.670	0.793	0.606	0.612	0.804
US4	0.568	0.530	0.464	0.544	0.570	0.781
US5	0.517	0.437	0.511	0.410	0.436	0.812

Model Evaluation and Fit

The evaluation of the model fit indicates that the measurement model is appropriate and meets the required thresholds for goodness-of-fit indices. The CMIN/DF value is 3.353, which is within the acceptable range, indicating a good fit between the data and the model. The Standardized Root Mean Square Residual (SRMR) is 0.07, which is excellent as it is below the target threshold of 0.08. Additionally, the Root Mean Square Error of Approximation (RMSEA) is 0.056, well below the target threshold of 0.08, further confirming an acceptable model fit. The Comparative Fit Index (CFI) is 0.911, and the Goodness of Fit Index (GFI) is 0.922, both exceeding the threshold of 0.80, indicating that the model adequately explains the observed data.

The analysis reveals a significant association between the independent variables—Passion (PA), Customer Engagement (CE), Relative Advantage (RA), Usability (US), and Perceived Interactivity (PI)—and the dependent variable, Sustainable Consumption Behavior (SCB). These results demonstrate that the model effectively captures the relationships hypothesized in the study, validating the theoretical framework.

Reliability and Validity Test

The psychometric properties of the constructs were evaluated through tests of internal consistency and validity. The results, presented in Table 4 (Cronbach's alpha), indicate that the Cronbach's alpha coefficient exceeds 0.60 for all dimensions, demonstrating strong internal consistency. According to guidelines provided by Hair et al. (2013) and Harandi et al. (2018), these values confirm the reliability of the assigned constructs.

The findings validate that the measurement items are robust and reliable for assessing the constructs under investigation, ensuring their suitability for further data analysis and hypothesis testing.

Table 4 Cronbach's alpha coefficient (α).

Dimensions	No. of Items	Cronbach's alpha
PA	6	0.877
US	5	0.822
CE	4	0.755
RA	6	0.825
PI	4	0.842
SCB	4	0.744
Total	29	

Convergent Validity

The study also evaluated convergent validity to ensure the constructs correspond accurately with related measures. Factor loading estimates and Average Variance Extracted (AVE) were used as the primary indicators. Convergent validity is demonstrated when AVE values exceed 0.50, indicating that a substantial portion of the variance in the indicators is explained by the constructs.

As shown in Table 5 (Construct Validity), all outer loadings of the reflective constructs are above the minimum threshold value of 0.60, with most exceeding 0.70, signifying strong item reliability. According to Lowry and Gaskin (2014), factor loadings between 0.60 and 0.70 are considered good, while values above 0.70 are very good. Thus, the factor loadings for all constructs fall within the acceptable range, further validating the model.

Table 5 Construct Validity

Construct	Items	Standard Loading	AVE
PA	PA1	0.760	0.621
	PA2	0.771	
	PA3	0.785	
	PA4	0.792	
	PA5	0.814	
	PA6	0.824	
US	US1	0.708	0.582
	US2	0.770	
	US3	0.804	
	US4	0.781	
	US5	0.812	
CE	CE1	0.790	0.575
	CE2	0.755	
	CE3	0.793	
	CE4	0.844	
RA	RA1	0.771	0.539
	RA2	0.773	
	RA3	0.782	

	RA4	0.824	
	RA5	0.776	
	RA6	0.735	
PI	PI1	0.793	0.681
	PI2	0.826	
	PI3	0.817	
	PI4	0.811	
SCB	SCB1	0.813	0.553
	SCB2	0.827	
	SCB3	0.775	
	SCB4	0.783	

Discriminant Validity

Discriminant validity was assessed using the cross-loading criterion and the Fornell and Larcker (1981) criterion. These measures ensure that constructs are distinct and not excessively correlated with one another.As shown in Table 6 (Correlation and Discriminant Validity), the correlations among the latent variables confirm discriminant validity. Specifically, the values on the main diagonal (representing the square root of the AVE for each construct) are higher than the correlations between each construct and all other constructs. This result demonstrates that each construct is more strongly associated with its own indicators than with those of other constructs, satisfying the requirements for discriminant validity.

Table 6 Correlation and Discriminant Validity

	Customer Engagement	**Passion**	**Perceived Interactivity**	**Relative Advantage**	**SCB**	**Usability**
Customer Engagement	0.759					
Passion	0.710	0.788				
Perceived Interactivity	0.603	0.763	0.825			
Relative Advantage	0.651	0.723	0.700	0.734		
SCB	0.487	0.536	0.539	0.512	0.743	
Usability	0.559	0.716	0.724	0.760	0.619	0.763

PLS-SEM Model Assessment

The evaluation of the Partial Least Squares Structural Equation Modeling (PLS-SEM) model was conducted using R^2 and Q^2 values to determine the model's prediction accuracy and predictive relevance.R^2, which measures the proportion of variance explained by the model for each endogenous construct, serves as an indicator of prediction accuracy. Higher R^2 values suggest that the model accounts for a significant portion of the variance in the constructs. In contrast, Q^2 evaluates predictive relevance, with values greater than zero indicating that the model is predictively relevant for a specific construct (Hair et al., 2013).

The results reveal strong predictive performance across the variables. For the Relative Advantage (RA) construct, the model demonstrates high prediction accuracy and relevance with $R^2 = 0.700$ and $Q^2 = 0.698$. Similarly, for Perceived Interactivity (PI), the values are $R^2 = 0.647$ and $Q^2 = 0.645$, indicating robust predictive strength. The Customer Engagement (CE) construct also exhibits adequate prediction accuracy and relevance with $R^2 = 0.509$ and $Q^2 = 0.501$. Finally, for Sustainable Consumption Behavior (SCB), the model achieves acceptable predictive performance with $R^2 = 0.336$ and $Q^2 = 0.351$.

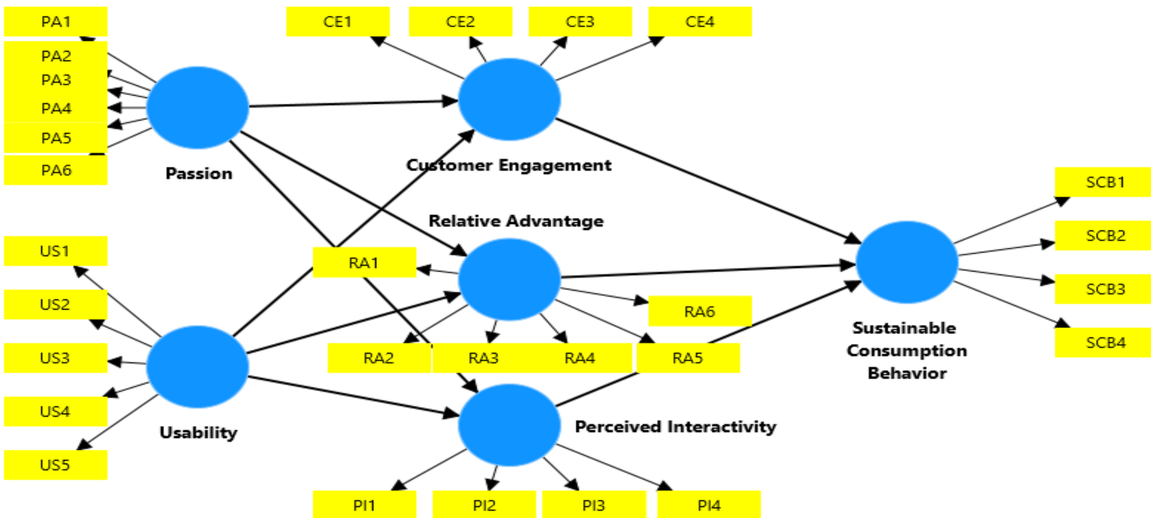

Figure 2 PLS-SEM Structural Model

Bootstrapping and Path Analysis

The Bootstrapping approach was utilized to assess the significance of the path coefficients in the PLS-SEM Structural Model. A two-tailed test was conducted with 5,000 samples at a significance level of 5%, ensuring 95% confidence intervals for the analysis.The proposed causal paths were computed to evaluate the structural relationships within the model. As shown in Figure 1 (PLS-SEM Structural Model), all hypotheses were confirmed. The results, presented in Table 7 (Path Analysis Results), indicate that both passion and usability have a significant and positive impact on sustainable customer behavior (SCB).These findings validate the theoretical model and confirm that the structural links among the constructs align with the proposed hypotheses. The results provide robust evidence that passion and usability are key drivers of sustainable consumption behavior, supporting all hypothesized relationships.

Table 7 Path Analysis Results

Hypothesis	**Paths**	**Total effects (coefficients)**	**Two-tailed test**
H1	Passion ->Customer Engagement	0.635	11.948
H2	Passion ->Perceived Interactivity	0.503	11.158
H3	Passion ->Relative Advantage	0.480	10.618
H4	Usability ->Customer Engagement	0.104	1.779
H5	Usability -> Perceived Interactivity	0.364	7.294
H6	Usability ->Relative Advantage	0.423	9.501
H7	Perceived Interactivity ->Sustainable _Consumption_Behavior	0.310	3.905
H8	Relative Advantage -> Sustainable _Consumption_Behavior	0.119	1.556
H9	Customer Engagement -> Sustainable _Consumption_Behavior	0.222	3.683

Mediation Analysis

To test the mediation effects within the model, the Bootstrapping approach recommended by Picon et al. (2014) was employed. This method involves analyzing 5,000 samples for the mediator variables at a 95% confidence interval, ensuring robust statistical inference.The analysis of specific indirect effects for each mediator is presented in Table 8, while the total indirect effects for the three mediators—Customer Engagement, Relative Advantage, and Perceived Interactivity—are shown in Table 9. The results indicate that the indirect effects for each construct are significant, confirming the mediation role of these variables. Furthermore, the total effect, which accounts for all mediators, is also significant, demonstrating complementary partial mediation within the model.

Table 8: Specific Indirect Effects

	Specific indirect effects	**Two-tailed test**
Passion ->Relative Advantage ->Sustainable _Consumption_Behavior	0.057	0.036
Passion ->Perceived Interactivity -> Sustainable _Consumption_Behavior	0.156	0.042
Passion ->Customer Engagement -> Sustainable _Consumption_Behavior	0.141	0.040
Usability -> Relative Advantage -> Sustainable _Consumption_Behavior	0.050	0.034
Usability ->Perceived Interactivity -> Sustainable _Consumption_Behavior	0.113	0.034
Usability ->Customer Engagement -> Sustainable _Consumption_Behavior	0.023	0.016

Table 9: Total Indirect Effects

	Total indirect effects	**Two-tailed test**
Usability -> Sustainable _Consumption_Behavior	0.186	5.489
Passion -> Sustainable _Consumption_Behavior	0.354	8.380

Discussions

The findings of this study underscore the pivotal role of artificial intelligence (AI) stimuli in shaping sustainable consumption behaviors through mechanisms such as customer engagement and intelligent customer experiences. By integrating these results with existing literature, meaningful insights and practical implications emerge regarding the interplay between emotional and functional dimensions of AI-driven systems.

Emotional Dimensions: Passion and Perceived Interactivity

The results support H1, confirming that passion significantly influences perceived interactivity. Users who experience emotional attachment and enjoyment are more likely to perceive AI systems as engaging and interactive. This finding is consistent with Herrando et al. (2019), who argued that passion enriches user perceptions of interactivity by fostering personalized and meaningful interactions. Similarly, H2 highlights the role of passion in shaping perceived interactivity, further emphasizing emotional involvement as a driver of engagement. These findings align with So et al. (2016), who noted that the Passionvalue derived from passionate interactions strengthens user connections and loyalty. These insights emphasize the importance of incorporating emotionally engaging features into AI systems to deepen user relationships and sustain long-term engagement.

Functional Dimensions: Usability, Engagement, and Relative Advantage

The study validates H3, demonstrating that passion amplifies the perceived relative advantage of AI systems by highlighting their unique functionalities. This finding supports the arguments of Vallerand et al. (2003) and Lavigne et al. (2012), who noted the influence of emotional investment on perceived superiority. In parallel, H4 and H5 emphasize the role of usability in fostering perceived interactivity and customer engagement. Intuitive and user-friendly systems enable seamless interactions, enhancing interactivity perceptions and encouraging frequent use, which fosters stronger customer loyalty (Zhang et al., 2014; Gao & Bai, 2014). Furthermore, H6 demonstrates that high usability enhances relative advantage, ensuring efficient service delivery, minimizing errors, and boosting user satisfaction (Flavian et al., 2006). Collectively, these findings illustrate the interplay between emotional and functional dimensions in driving the adoption and sustained use of AI systems.

Mediating Roles and Sustainable Consumption

The results highlight how mediating variables such as perceived interactivity, relative advantage, and customer engagement influence sustainable behaviors. H7 confirms that perceived interactivity promotes sustainable consumption by immersing users in engaging and responsible patterns of usage. Tailored experiences build trust and commitment to sustainability goals, as emphasized by Cao and Liu (2023). Similarly, H8 shows that recognizing the relative advantages of AI systems—such as efficiency and eco-friendly functionalities—encourages sustainable behaviors (Trawnih et al., 2022). H9 further demonstrates that customer engagement drives sustainable consumption by aligning users' emotional and behavioral investments with sustainability objectives (Piligrimienė et al., 2020). These findings underscore the importance of leveraging functionality, interactivity, and engagement to inspire eco-conscious behaviors.

Indirect Effects and Pathways to Sustainability

The study reveals intricate pathways connecting usability, passion, interactivity, and engagement to sustainable consumption behaviors. H10 confirms that customer engagement partially mediates the relationship between perceived interactivity and value co-creation, emphasizing the role of interactive platforms in shaping outcomes (Brodie et al., 2011). H11 and H12 highlight the mediating effects of relative advantage and perceived interactivity, respectively, in linking passion to sustainable consumption. Passionate users are more likely to engage deeply with eco-conscious systems, translating emotional investment into actionable behaviors (Yang et al., 2024). Similarly, H13 illustrates how customer engagement bridges passion and sustainable consumption, demonstrating how emotional alignment with sustainability goals fosters meaningful practices (So et al., 2016).H14 and H15 show that usability indirectly influences sustainable behaviors through relative advantage and perceived interactivity, respectively. Intuitive systems highlight their benefits, enhancing user satisfaction and promoting sustainable actions (Flavian et al., 2006; Gao & Bai, 2014).

Conclusion

This study highlights the transformative potential of artificial intelligence (AI) in promoting sustainable consumption behaviorsthrough customer engagement and intelligent experiences. It offers valuable insights for practitioners seeking to integrate sustainability into their digital strategies and contributes to the theoretical understanding of how AI influences consumer behavior.

Theoretical Contribution

The research extends the stimulus-organization-response (SOR) model and Theory of Planned Behavior (TPB) by examining how AI stimuli influence sustainable consumption behaviors. It underscores the mediating roles of passion, usability, customer engagement, and perceived interactivity in linking AI features to eco-conscious practices. By integrating emotional (hedonic) and functional (usability) factors, the study provides a multidimensional perspective on the role of AI in shaping consumer decision-making. It also fills a gap in research on technology-driven sustainability frameworks by emphasizing the importance of interactive and personalized systems in fostering environmentally responsible behaviors.

Practical Contribution

This study offers actionable strategies for organizations to incorporate sustainability into their AI-enabled operations. Interactive and personalized AI systems can strengthen emotional connections, encouraging consumers to engage with eco-conscious products and services (Ameen et al., 2020). By improving usability and perceived interactivity, companies can build trust and encourage repeat engagement with sustainable platforms, promoting responsible consumption behaviors (Nazir et al., 2023). Additionally, AI-driven features such as virtual assistants and personalized recommendations can subtly promote energy-saving and eco-friendly practices, aligning corporate social responsibility goals with environmental objectives. These findings stress the importance of aligning digital strategies with sustainability initiatives to create meaningful environmental and social impacts.

Limitations

Despite its contributions, the study has limitations. The focus on a specific demographic—Gen Z consumers in Egypt—may limit the generalizability of the findings to other cultural or geographical contexts. Additionally, the reliance on self-reported data introduces potential biases, such as socially desirable responses about sustainable behaviors. The cross-sectional design further restricts the ability to assess long-term impacts of AI stimuli on consumer behavior, limiting the scope for understanding changes over time.

Future Research Directions

Future studies could adopt longitudinal designs to explore how AI stimuli influence sustainable behaviors over time, offering insights into the evolution of consumer engagement. Cross-cultural comparisons could examine the role of socio-cultural factors, broadening the understanding of how diverse consumer groups interact with AI systems (Lazaric et al., 2020). Expanding the framework to include constructs such as perceived risks, ethical considerations, and trust in AI systems would enhance the comprehensiveness of the model. Furthermore, with the advent of generative AI and blockchain-enabled platforms, future research should investigate their potential impacts on sustainability practices to remain aligned with technological advancements.

Final Thoughts

The study's theoretical and practical contributions emphasize the significant potential of AI in shaping sustainable consumption patterns. By fostering a deeper alignment between technology and environmental goals, AI can act as a catalyst for more responsible consumer behaviors, paving the way for a more sustainable future.

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