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From Pixels to Plates: Exploring AI Stimuli and Digital Engagement in Reducing Food Waste Behavior in Lithuania Among Generation Z and Y

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Abstract

The global issue of food waste is a significant concern due to its extensive social, economic, and environmental repercussions. To attain our sustainable future objectives, we must confront the food waste challenge directly. This study, grounded on the Stimulus–Organism–Response (S-O-R) theoretical framework, examines the impact of AI-based stimuli—passion, usability, perceived personalization, and perceived interactivity—on users' intentions of minimizing food waste. Social presence and psychological engagement signify internal organism (O) states, while self-efficacy acts as the moderating factor between these organism states and intention (R). Data were gathered via Computer-Assisted Web Interviewing (CAWI) in a stratified quota sample of 315 participants in Lithuania, concentrating on Generation Y and Millennial Generation Z consumers of the Samsung Food app, aimed at promoting food waste reduction. Participants were pre-screened and recruited via several means to guarantee an adequate sample. The results indicate that passion, usability, and perceived interactivity substantially influence social presence and psychological engagement. Nonetheless, these organism-level variables did not have an immediate impact on behavioral intention, and all indirect (mediated) effects from stimulus response were significantly rejected. Conversely, self-efficacy considerably influenced the association between social presence and psychological engagement with intention, indicating that enhanced user confidence enhances the possibility of turning engagement into behavioral responses. This study features generational differences between Y and Z and only found significant interaction between perceived personalization and social presence in Generation Y, as compared to Generation Z. This work extends the literature on AI-driven behavior modification by asserting that mere involvement is inadequate. Enabling consumers by enhancing self-efficacy is crucial for developing viable AI-based applications that encourage sustainable customer behavior.

Keywords: intention to reduce food waste; passion; usability; perceived interactivity; perceived personalization; social presence; psychological engagement; self-efficacy

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1. Introduction

Food waste is a global problem that affects social, environmental, and economic sectors, creating many complex issues [1,2]. Almost one-third of the food produced worldwide (i.e., 1.3 billion tons per year) is wasted, resulting in an annual financial loss of approximately USD 750 billion [3]. Conversely, research data shows that about 800 million people are

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hungry or have no food to eat [3,4]. In the European Union (EU) alone, 59 million tons of food are wasted each year, which is 131 kg per person in a food market with an estimated value of EUR 132 billion [5]. In response, the EU has introduced measures under the Farm to Fork Strategy and the Waste Framework Directive that encourage consumers to consume sustainably, reduce waste, and use food more efficiently. As the European Green Deal sets out, these initiatives align with the EU's target of reducing food waste by 50% by 2030 [6,7].

The issue of food waste has been receiving increased attention in recent years; however, there remain significant research gaps regarding the relative scale and characteristics of food waste in different European countries [8,9]. The EU's current Farm to Fork Strategy and Circular Economy Action Plan advocate for uniform targets, yet research reveals significant regional disparities in food waste drivers and patterns. For instance, Eastern European member states such as Latvia, Lithuania, Poland, Romania, and Slovakia face higher post-harvest losses due to infrastructural gaps, while Western European countries such as Belgium, Austria, Germany, the Netherlands, and Switzerland's waste stems predominantly from consumer behavior [10]. Compared to other Eastern European countries, research on food waste in Lithuania includes only a small number of studies on consumer behavior and food waste, as well as on the amount of food that ends up in the trash. The most recent study on food waste conducted by Eičaitė, O. and T. Baležentis [11] mentioned that Lithuania has a high level of household food waste, averaging 74.5 kg per person annually, driven by avoidable factors like spoilage, over-preparation, and poor food management. There remains a significant national-level research gap in comprehensively addressing food waste in the Lithuanian context.

In-depth research on food waste behavior (FWB) has illuminated a wide range of factors that influence consumer waste practices. Past studies have mentioned the influence of self-identity, consumer attitude, perceived time constraints, and over-purchasing, all of which shape food waste behavior [12]. Emotional aspects, involving negative emotions such as guilt and positive emotions such as pride, have been identified as powerful factors in reducing food waste [13–15]. Other important factors include religiosity [16], environmental concern, personal norms [17], moral perspective [18], and shopping routines [19–21]. Furthermore, sociodemographic variables such as age, gender, employment status, and family size have an influence on food waste-related behavior [22–24]. Moreover, sociological frameworks emphasize the role of social routines, cultural norms, and structural constraints that shape food waste behavior in ways that often go beyond individual control [25–27].

Even with the expanding literature, there remains a critical gap in understanding how new technologies, particularly artificial intelligence (AI), can be used to influence or reduce food waste behavior. AI has shown transformative potential in various industries, such as healthcare [28,29], personalized marketing [30,31], higher education [32,33], and agriculture [34,35]. In the food sector, AI technologies offer promising solutions, including intelligent inventory management, automated waste tracking, predictive analytics for meal planning, and personalized insights into consumer behavior [36–38]. For example, AI-powered apps and systems suggest recipes based on expiring ingredients, while smart refrigerators can monitor food inventory and minimize waste [39,40]. In addition, AI systems that provide timely reminders, consumption data, or personalized recommendations improve individuals' perceived control over food management, thereby reducing waste [41,42]. However, beyond the functional utility of AI tools, there is a lack of empirical research on how AI-driven users experience features, particularly psychological and social interaction factors, that influence actual behavioral change in the context of food waste.

In addition, self-efficacy—defined as a person's belief in their ability to perform certain behaviors—is of importance [43]. Individuals with high self-efficacy are more likely to strive for responsible consumption and exhibit approach-oriented rather than avoidant behavior. Although previous studies have identified self-efficacy as a key factor in pro-environmental intention, including food waste behavior [43–46], its moderating role between social presence, psychological engagement, and behavioral outcomes remains underexplored in the context of food waste.

Age has repeatedly emerged as a crucial sociodemographic variable for understanding differences in sustainable consumer behavior [47]. In terms of digital engagement, younger cohorts (e.g., Gen Z, Gen Y) show greater digital affinity than older ones [48]. Generational differences not only influence the acceptance of AI-based technologies but also values regarding sustainability, data sharing, and information-seeking behavior [49]. These generational differences also point to the potential for different attitudes and behaviors related to food waste. However, empirical studies that explicitly examine food waste behavior across generations remain scarce. While AI technologies are increasingly integrated into digital platforms to promote sustainable consumption, there is a significant gap in empirical research on how AI-driven users experience features, particularly those with psychological and social interaction mechanisms, that influence actual behavioral changes in reducing food waste.

This study closes this gap by introducing the Stimulus–Organism–Response (S-O-R) model. The S-O-R theory is based on behaviorism, which explains the relationship between stimuli and responses. The goal is to investigate how AI stimuli—passion, usability, perceived interactivity, and perceived personalization—act as external stimuli that influence internal psychological states such as social presence and psychological engagement, ultimately influencing food waste behavior. Previous research has confirmed these dimensions of AI user experience in domains such as e-commerce, gaming, and digital learning [50,51]. However, little research has been conducted on their application in food management. Passion refers to the emotional connection users feel with AI systems, which can promote engagement and repeated use, while usability affects user-friendliness and encourages regular use [52]. Perceived interactivity reflects the extent to which users feel that their inputs are perceived and responded to by the system, while perceived personalization reflects the extent to which AI tools adapt responses and recommendations to individual needs [53,54].

These AI design features have been proposed to enhance social presence—the perception of human-like interactions—and psychological engagement, including attention, involvement, and emotional investment. These internal mechanisms are believed to combine to influence pro-environmental behavior, especially the reduction of food waste. Previous studies have investigated the generational difference between Generation Y and Generation Z in sustainable research [55], but their behavioral response to AI-driven interventions for food waste has not been adequately investigated. Accordingly, this study attempts to address the following research questions:

RQ1: Are there substantial relationships between AI stimuli (passion, usability, perceived interactivity, and perceived personalization) and food waste behavior?

RQ2: Is there a significant relationship between social presence and psychological engagement (as organismic factors) and actual food waste behavior?

RQ3: What mediating mechanisms underlie the relationship between AI stimuli and food waste behavior, particularly through social presence and psychological engagement?

RQ4: Does self-efficacy moderate the relationship between social presence, psychological engagement, and food waste behavior?

This study makes five important contributions to the literature on food waste behavior and digital sustainability. First, it extends existing behavioral research by examining how AI-driven user experience (UX) characteristics—passion, ease of use, perceived interactivity, and perceived personalization—influence actual food waste behavior, a dimension largely

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overlooked in previous studies. Second, it introduces social presence and psychological engagement as mediators, thus offering a new perspective on the mechanisms through which AI stimuli influence sustainable behavior. Third, this study addresses persistent empirical gaps by focusing on Eastern Europe, particularly Lithuania, where consumer food waste behavior remains understudied despite alarming waste levels. Fourthly, this study contributes to the theoretical development of digital behavior models by examining the moderating role of self-efficacy, emphasizing how individuals' confidence in their ability to act influences the conversion of psychological and social experiences into actual behavioral change regarding food waste. Finally, it adds a critical generational perspective by examining how age cohorts moderate responses to AI-driven sustainability interventions, thus influencing the development of age-appropriate digital strategies to reduce food waste.

2. Literature Review and Hypothesis

2.1. S-O-R (Stimulus–Organism–Response) Theoretical Framework

The S-O-R theory was proposed by Berlo and Gulley in 1957 and evolved from the Stimulus–Response (S-R) theory based on behaviorism, which explains the relationship between stimuli and responses [56]. The S-O-R theory specifies individual behavior in response to specific stimuli, and the theory overlooks logical reasoning in the process of explaining responses. According to [57], the unique and primary strength of the S-O-R framework is flexibility, as it can be used to examine numerous internal and external stimuli; tangible and intangible stimuli; and experiential and non-experiential organisms.

S-O-R recommends the disclosure of external factors (S) for individuals who have initiated inner motions (O) that are central to a resulting behavior (R) [58,59]. In the proposed framework, this study applies the Stimulus–Organism–Response (S-O-R) theory to examine how AI stimuli function as external factors (S) encountered by consumers during front-line interactions with AI-based applications. It considers self-efficacy and psychological behavior as organism variables (O), reflecting consumers' strong engagement in reducing food waste, and actual food waste behavior as the response (R). In the fields of AI and information systems, numerous studies have employed the S-O-R model to capture various external stimuli such as AI passion, usability, security features, interactivity, personalization, and perceived value [60–63], as well as organism variables like social value, emotional value, and perceived value [61,64], to predict consumer approach behaviors. Within the Stimulus–Organism–Response (S-O-R) context, there still exists an extensive gap in the literature concerning food waste, essentially considering contemporary innovations in artificial intelligence. Despite the cumulative integration of AI into consumers' daily lives, limited studies have explored how these interactions impact consumption behaviors that contribute to food waste. Examining the role of self-efficacy and psychological factors in shaping consumer responses to AI-driven stimuli is crucial for developing a deeper understanding of food waste behavior from the current technological perspective.

2.2. AI Stimuli and Intentions to Reduce Food Waste

AI and digital technology have greatly influenced the behavior of consumers [65]. Research has demonstrated that when AI systems are tailored to human emotional and cognitive needs, there is a considerable improvement in collaborative productivity and effectiveness [66]. Stimuli are those that impact the internal state of an individual and can be rationalized as those that stimulate action or facilitate action [58], and AI stimuli are the consumer's sense of happiness and usability while utilizing AI technology [67]. Passion and usability are conspicuous stimuli of artificial intelligence and have promoted sustainable consumption behavior [61]. The research indicates that both emotional (passion) and functional (usability) AI attributes substantially affect eco-conscious behaviors via customer engagement and intelligent experiences [68]. The study conducted by [69] resulted in the finding that the hedonic and utilitarian aspects of the digital app have a significant impact on the consumers' trust in the digital app and their relationship to food safety.

2.3. Passion and Social Presence

Cao and Liu [61] found that passion is a significant motivator of artificial intelligence and has fostered sustainable consumption behavior. Hedonic stimulation encompasses passion, characterized by consumers experiencing pleasant feelings and emotions during interactions associated with the pursuit of pleasure [70]. The study concluded that emotional indicators of chatbots can influence the sense of their humanness via social presence [71], while the online meal delivery app, Dutta, K. et al. [69], demonstrates that hedonic factors have impacted consumer trust in digital applications and food safety. In the present study, users of AI-based applications contributed to the reduction of food waste and the mitigation of consumption activities related to food waste, thereby tangibly benefiting the world. This beneficial, self-esteem-oriented approach of AI applications provides users with a positive experience and emotion, increases awareness of food waste, and boosts consumer awareness of the utility of AI-based applications. An individual with an elevated capacity for emotional contagion possesses a profound sense of affective social presence and is more inclined to become a follower of AI-based applications. In summary, based on the literature review, we suggest the following hypothesis:

H1: *AI stimulus passion positively influences social presence.*

2.4. Passion and Psychological Engagement

Passion is a potent motivator of artificial intelligence [61] that leads individuals to pursue tasks with intense excitement and perseverance. In the context of AI platforms, passion can dramatically influence psychological engagement by establishing a sense of connection and purpose in user experiences. When consumers are passionate about a particular activity, such as engaging with AI-based nutrition applications, they are more likely to immerse themselves fully in these activities, and the research indicates that materialism, pleasure, and social acceptance positively impact Generation Z's psychological involvement [72]. Further, research has demonstrated that participants have a heightened relationship to content that resonates with their emotions, thus reinforcing the significance of empathy in augmenting user engagement [73,74]. Ultimately, feeding users' passion through well-designed interfaces and meaningful interactions can generate a cycle of continuous engagement and long-term adoption. Based on the above discussion, the following hypothesis is suggested:

H2: *AI stimulus passion positively influences psychological engagement.*

2.5. Usability and Social Presence

Cao and Liu [61] concluded that usability is a conspicuous stimulus of artificial intelligence and promotes sustainable consumption behavior. The usability of mobile app prototype developments resulted in adolescents liking to practice the mobile app's various usability functionalities, particularly those associated with achieving individual and team-based goals for choosing healthier food choices and less consumption [75]. The adoption of an AI-based application satisfies both team objectives and individual accomplishments by promoting realistic food consumption behaviors aligned with UN SDG 12 while also facilitating healthier food choices that meet individual preferences.

The AI-based platform provides attractive environments with high-quality food details, and research confirms that platforms that provide substantial immersion via realistic graphics, sound, and haptic input create a sense of physical presence in the virtual environment, hence augmenting social presence and engagement [76,77]. Utilitarian stimulation talks about usability, and the study of perceived value (utilitarian, social, and hedonic) of humanoid social robots indicates a significant impact on user satisfaction [60]. Thus, we hypothesize the following:

H3: *AI stimulus usability positively influences social presence.*

2.6. Usability and Psychological Engagement

A considerable corpus of research underlines the crucial significance of usability in fostering psychological engagement inside AI-driven digital platforms. As the utilitarian stimulation encompasses usability, and the study by [69] indicates that a significant element affecting consumers' trust in digital applications and food safety is the utilitarian approach adopted by the online meal delivery app, the app based on AI must include a user-friendly interface to enable effortless navigation and promote consistent usage. In AI-driven nutrition platforms, usability underscores the significance of intuitive design for user engagement [78]. Enhanced usability has garnered increased engagement [79], and intuitive design has proven to be crucial for user engagement. Therefore, bolstering usability with intuitive design appears as a vital method for improving psychological involvement in AI-powered applications. Based on the above discussion, the following hypothesis is suggested:

H4: *AI stimulus usability positively influences psychological engagement.*

2.7. Perceived Personalization and Social Presence

Personalization is vital in nurturing positive attitudes and reinforcing interpersonal connections [80]. Research indicates that personalization is the most significant factor influencing the perceived value of voice assistants, with social presence augmenting this personalization [81]. Another study shows that enhanced personalization options augment users' sense of control, hence elevating their social presence [82]. The dialogue between AI devices and users exhibits a crucial human-like characteristic that generates a sense of social presence in the consumer's awareness, prompting interaction with these artificial agents as one would with humans [83]. Due to recent technological advancements, humans are becoming progressively habituated to engaging in quasi-social connections with AI entities [84]. Humans are inherently social beings, so when a technology or gadget elicits a sense of social presence, they tend to apply social norms to the contact, such as exhibiting courtesy and pausing for responses, like interpersonal exchanges [85]. Specifically, it has been imagined that AI-based apps evoke sensations of social presence; hence, when consumers receive personalized recommendations from an AI-based app, they are inclined to employ the same social norms as they would when receiving suggestions from a human being. An AI-based app for sustainable food waste has delivered a personalized service of planning and consuming outlines to each consumer as per their setting constraints for the daily food use and accumulated spending of the consumers that they have claimed. In this context, social presence may cause consumers to view the AI-based app as a genuine individual providing tailored advice, and the proposed hypothesis is as follows:

H5: *AI stimulus perceived personalization positively influences social presence.*

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2.8. Perceived Personalization and Psychological Engagement

Perceived personalization refers to consumers' beliefs regarding services, products, or initiatives tailored to their specific habits, requirements, and preferences. Research has indicated that personalization has a significant impact [51], and personalized campaigns influence consumers to act contrary to their desires [86]. The AI-based app offers several forms of food personalization, including tailored nutrition regimens, bespoke meal recommendations, calorie assessments, and food safety identification. The current study used an AI-based app providing food choices with an AI-based meal planner, overall consumption of food with estimation, available stock, and expired ones. So, when consumers perceive meal plans or recommendations of food as per their personalized preferences, they are engaged more and experience sophisticated contentment. This engagement leads the consumers toward significant food waste behavior. Based on the findings of the experimental investigation of leisure engagement, Ref. [87] concluded that personalization contributes to higher engagement. The research confirms that AI-based personalization has positively influenced consumer engagement [88,89]; this engagement leads to a robust emotional connection with the services. Yet, the current study's main objective is to investigate how AI-driven personalization has impacted actual consumer behavior regarding food waste within the mediating effect of the psychological engagement of AI-based apps, and the following hypothesis is proposed:

H6: *AI stimulus perceived personalization positively influences psychological engagement.*

2.9. Perceived Interactivity and Social Presence

Interactivity within the digital world provides consumers with an enormous attraction that transcends the ability of passive segregation of the traditional user [90]. Research shows that platforms that promote high interactivity, such as social media and online gaming, augment social presence by enabling significant interaction and engagement among young users [91], while a study on AI chatbots indicates that social presence impacts the association between anthropomorphic characteristics and users' perceived quality of interactions [92]. This indicates that interaction is a vital method for promoting an improved sense of social presence. Increased perceptions of social presence lead users to regard interactions as genuine, human-like, and emotionally fulfilling. Thus, this notion may result in enhanced user loyalty, elevated satisfaction, and ultimately, larger platform adoption. Consequently, promoting interactivity is a crucial approach for digital platforms aiming to enhance social presence and enrich user experience. This study proposes to examine perceived interaction with the mediating influence of social presence within AI-based systems. Thus, we hypothesize the following:

H7: *AI stimulus perceived interactivity positively influences social presence.*

2.10. Perceived Interactivity and Psychological Engagement

It is observed that interactivity perceived by users has significantly stimulated the psychological intention of the user, which is within the controllability and playability aspect, and has affected their behavioral intention [93]. The combination of mobile application design elements and user interactivity formulas, and inclusive interactivity amalgamated with user-customized information, has created an amusing flow experience [94]. Perceived interactivity has an instant connection between AI technology and the consumer and has the capability of responding as per their claim. The similar bustle in the Ant Forest app finds that user interactivity has a positive influence on sustainable consumption behavior [95], and perceived interactivity has a significant impact on consumer engagement [51]. Thus, in the AI context, the proposed hypothesis is as follows:

H8: *AI stimulus perceived interactivity positively influences psychological engagement.*

2.11. Mediating Effect of Social Presence

According to social response theory, when machines behave like humans (AI), users interact with them in a human-like manner [96]. A social presence (SP) arises when the customer is unaware of the quasi-authenticity of humans or the humanity of non-human social actors in a transitional situation. Social presence makes consumers feel that they are in the company of another social entity [83] and imitates the emotions that other people bring to individuals. These emotions are the medium or attribute that users have felt due to the medium.

Short [97] demonstrates SP as a measurable degree of individuals' interpersonal prominence in social media, or sense of contact with other people [98], like a human–machine contact in the perspective of human–computer interaction [99], and in the current scenario, human–AI interaction. Other researchers have argued that SP cannot be determined exclusively by the capacity of the medium because it is a state of mind [100]. Researchers have emphasized the significance of social presence in relationships with technology to ascertain its auspicious impact on consumer behavior [101,102]. This study defines social presence as the feelings of customers while interacting with an AI-enabled mobile app, which will bring a more distinctive sense to them than interaction with humans. When a consumer interacts with an AI-based app, it is reasonable to assume that they will seek assistance from the app to decide their consumption behavior if the encounter appears to be warm, welcoming, and interactive with relevant information. The consumption decision's reasoning that social values influence behavior is reflected in this assumption. The study also confirms that social presence enhances positive behaviors in virtual reality [103].

Additionally, the S-O-R model's notion that external stimuli (PU, PP, usability, and passion) undoubtedly affect users' internal states (social presence), ultimately leading to beneficial behavioral reactions, is reflected. In accordance with this, research confirms that SP partially mediates the influence of AI stimuli on customer stickiness [62]. In summary, based on the literature review, we suggest the following hypothesis:

H9: *Social presence positively affects intentions not to waste food.*

H11(a): *Social presence mediates the relationship between AI stimulus passion and intentions to reduce food waste.*

H11(b): *Social presence significantly mediates the relationship between AI stimulus usability and intentions to reduce food waste.*

H11(c): *Social presence significantly mediates the relationship between AI stimulus perceived personalization and intentions to reduce food waste.*

H11(d): *Social presence significantly mediates the relationship between AI stimulus perceived interactivity and intentions to reduce food waste.*

2.12. Mediating Effect of Psychological Engagement

Psychological engagement is the enjoyment level and perceived importance that are believed to rise during activity. When individuals have reached the engagement state, they become fully involved in an activity and have established a robust attention and sensation for it [87]. Ref. [104] proposed a revised categorization of psychological engagement, encompassing cognitive, affective, and relational/spiritual components of involvement.

Ellis and Jiang [87] concluded from the experimental study of leisure engagement that provocation, personalization, and cohesion have increased engagement. The mediating role of psychological engagement is positively justified by leisure crafting and pro-environmental behavior [105]. Research concluded that within the realm of e-commerce, AI directly and indirectly influenced psychological engagement, particularly observable engagement behaviors, and that psychological engagement positively affected the efficacy of recommendation systems [89,106]. Ref. [59] confirmed that the electronic service quality practiced by consumers in the transaction of online shopping impacts both the psychological engagement and behavioral engagement of consumers. These studies support the examination of engagement, especially the psychology in the S-O-R paradigm, and offer a clear and actionable framework for understanding how AI stimuli in mobile apps lead to psychological and behavioral engagement. Psychological engagement occurs when consumer interaction is achieved with AI-based applications to gratify their intrinsic desires. Therefore, psychological engagement plays a crucial role in determining personal behavior toward food wastage. Based on the above discussion, the following hypothesis is suggested:

H10: *Psychological engagement positively affects the intention not to waste food.*

H12(a): *Psychological engagement mediates the relationship between AI stimulus passion and intentions to reduce food waste.*

H12(b): *Psychological engagement mediates the relationship between AI stimulus usability and intentions to reduce food waste.*

H12(c): *Psychological engagement mediates the relationship between AI stimulus perceived personalization and intentions to reduce food waste.*

H12(d): *Psychological engagement mediates the relationship between AI stimulus perceived interactivity and intentions to reduce food waste.*

2.13. Self-Efficacy as a Moderator

Self-efficacy is individual judgment, reliance, or confidence in one's own ability to accomplish a definite task at a particular level [107]. Self-efficacy is vigorous in leading persons' behavior and individuals' self-confidence in specific dimensions to achieve the established goals [100]. People who believe in high self-efficacy are more likely to adopt pro-environmental behavior in problem-solving or task performance [108] and instigate approach behavior rather than avoidance behavior [45]. So, when consumers meet several confusions, high self-efficacy individuals may not be delayed toward a positive decision of avoiding the waste of food, as they are inclined to move forward in the direction of the approach behavior rather than the avoidance behavior.

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The moderating role of self-efficacy in the light of the Stimulus–Organism–Response (S-O-R) model determined that it effectively moderates the influences of various confusions on decision postponement [109], and food consumer behavior in a digital context confirms that the mediating relationship of self-efficacy with online green interaction has significantly influenced the willingness to purchase green food [110]. Concerning restaurant patrons, it is affirmed that self-efficacy has facilitated food waste reduction and has positively impacted consumers' intentions to reduce food waste [45]. In the aforementioned context of self-efficacy, to assess their persistence in food waste behavior concerning "psychological engagement and social presence", the suggested hypotheses are as follows:

H13(a): *Self-efficacy moderates the relationship between social presence and intentions to reduce food waste.*

H13(b): *Self-efficacy moderates the relationship between psychological engagement and intentions to reduce food waste.*

2.14. Generation Y and Z as a Moderator

This research emphasizes significant generational gaps in food waste intentions between Generation Z (born 1997–2012) and Generation Y (born 1981–1996). Generation Z, also known as digital natives, exhibits heightened environmental awareness and a commitment to sustainability [111] as well as an intense digital affinity [48]. Examining Generation Z and Generation Y regarding food waste intentions is essential, especially in the realm of AI-driven stimuli, owing to their unique technological behaviors [112], food consumption patterns [113,114], and psychological reactions [115]. Research determined that throughout the epidemic, Generation X, Generation Y, and Generation Z assigned varying values to various aspects, particularly in food selection [113].

Both generations are devoted consumers of digital platforms and mobile apps, rendering them essential audiences for AI-driven initiatives designed to foster sustainable behavior. Research has emphasized the influence of AI-driven smart home appliances on adolescents, identifying perceived usefulness, ease of use, and social presence as the key factors for prospective users, particularly in shaping their intentions and actual usage [116].

Generation Z, born in a digital world, seeks immersive and engaging experiences, making them more susceptible to AI influences, including personalization, usability, passion-oriented content, and perceived interaction. Despite their technological competence, Generation Y values utility and effectiveness. The organism-level characteristics, like social presence and psychological involvement, are essential to understanding how these AI functionalities affect users across groups. Generational differences may translate organism-level experiences into behavioral intentions like reducing food waste. The moderating role of self-efficacy is key; confident people are more likely to act sustainably.

H1–H13(b): *Generation moderates the relationships in H1–H13(b) (there is a significant difference between Generation Y and Generation Z).*

Building on these hypotheses, we propose the theoretical model presented in Figure 1, illustrating how AI-driven stimuli (passion, usability, personalization, and interactivity) influence the intention not to waste food through the mediating roles of social presence and psychological engagement, with self-efficacy moderating these relationships.

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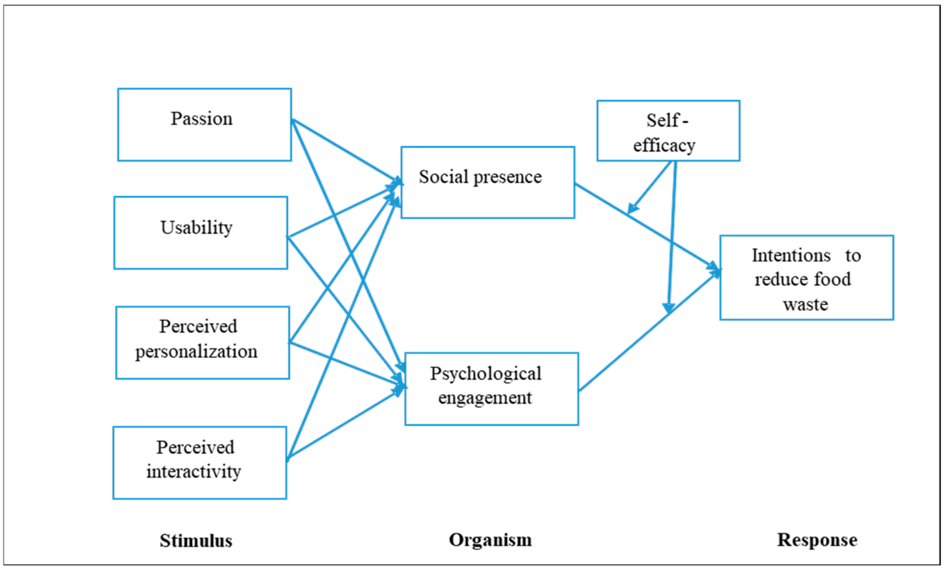

Figure 1. Conceptual model.

3. Materials and Methods

3.1. Data Collection

Data for this study were collected using Computer-Assisted Web Interviewing (CAWI) through a skilled online research panel, with a pre-screening process implemented to ensure respondent engagement. The survey questionnaire was developed, pre-tested, and digitally distributed among individuals from Generation Y (born 1981–1996) and Generation Z (born 1997–2012) living in Lithuania. A stratified quota sampling technique was employed to ensure a representative sample of the Lithuanian population, selecting approximately 315 potential respondents. These respondents were divided into two subgroups based on age, Generation Y and Generation Z, with quotas set to reflect the population distribution. Participants of the study were recruited through various communication channels: the internal research agency respondent database, targeted Facebook advertising, an online consumer panel, and collaboration with the Students' Association and the Language Service Provider (LSP) partnership program. This combination of channels allowed for reaching a broader audience and ensuring a sufficient sample size. A total of 315 finalized responses were acquired, and participants were told that their answers would be used for scholarly publishing in a way that kept their identities secret. Both generational groups have used the Samsung Food app, which is dedicated to reducing food waste behavior. This methodology supports robust conclusions about technology adoption and user preferences in Lithuania.

3.2. Measurement

All measures were adapted from the literature. For food waste behavior, to measure intention toward food waste, four items were adapted from [117–120]. Passion was measured with three items and was modified from Cao, P. and S. Liu; and Baldus, B.J., C. Voorhees, and R. Calantone [61,121], while for usability, three items were modified. For perceived personalization and perceived interactivity, four items were used for each and adapted from [62,122]. For social presence and psychological engagement, five items were used from [62,99,123] and [106,124], respectively. Self-efficacy was modified from [109,125] using three items. All research variables, excluding demographic information, were assessed utilizing a 7-point Likert scale, ranging from 7 (completely agree) to 1 (completely disagree).

3.3. Data Analysis

Reliability and Validity of the Measurement Instrument

Details of the demographic analysis are shown in Table 1. SPSS 26.0 and SmartPLS 4 were utilized to evaluate the reliability and validity of the measurement model in this study. Both Cronbach's alpha and composite reliability (CR) tests were performed to assess the structural reliability of the measurement model (see Table 2). The Cronbach's alpha values ranged between 0.767 and 0.906, and both tests exceeded the threshold of 0.7 [126]. The internal consistency of the measurement model was tested using the average variance extracted (AVE) and factor loading. Each respective factor loading was above 0.5 [127], and the AVE was above 0.5 [128], which shows high reliability and validity.

Table 1. Demographic details.

Category	Frequency	Percentage
Gender		
Male	238	76%
Female	76	24%
Other	2	1%
Age		
16–27	119	38%
28–43	196	62%
Education		
Basic primary education	9	3%
Secondary education	49	16%
Higher secondary education and special education	22	7%
College education	15	5%
Higher education (non-university level)	58	18%
Higher education (university level)	162	51%
Monthly Income		
No income	17	5%
Less than EUR 350	14	4%
EUR 351–450	9	3%
EUR 451–550	14	4%
EUR 551–750	13	4%
EUR 751–950	37	12%
EUR 951–1500	101	32%
EUR 1501–2000	70	22%
EUR 2001–2500	24	8%
EUR 2501–3000	8	3%
EUR 3001–4000	5	2%
EUR 4001 and above	3	1%

Table 2. Factor loading, Cronbach's alpha, composite reliability, and average variance extracted.

Variables	Items	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Passion			0.890	0.932	0.820
	PI1	0.899			
	PI2	0.922			
	PI3	0.905			
Usability			0.884	0.928	0.811
	U1	0.903			
	U2	0.921			
	U3	0.878			
Perceived Personalization			0.855	0.902	0.696
	PP1	0.843			
	PP2	0.842			
	PP3	0.825			
	PP4	0.828			
Perceived Interactivity			0.829	0.886	0.661
	PI1	0.782			
	PI2	0.823			
	PI3	0.817			
	PI4	0.829			
Social Presence			0.906	0.931	0.730
	SP1	0.882			
	SP2	0.740			
	SP3	0.862			
	SP4	0.891			
	SP5	0.886			
Psychological Engagement			0.767	0.864	0.682
	PE1	0.893			
	PE2	0.868			
	PE3	0.703			
Self-Efficacy					
	SE1	0.661			
	SE2	0.851			
	SE3	0.838			
Intentions to Reduce Food Waste			0.800	0.868	0.622
	I1	0.808			
	I2	0.739			
	I3	0.805			
	I4	0.799			

Discriminant validity denotes the degree to which a construct is genuinely separate from other constructs within a model (Figure 2), signifying that it assesses a concept that is distinct from the others. Table 3 demonstrates that all constructs satisfy the criteria for discriminant validity [129] as the square root of the AVEs for each construct surpasses the correlations with other constructs. In addition, the HTMT scores based on the HTMT 0.90 thresholds by Henseler et al. [130] are all below 0.90, further confirming the discriminant validity.

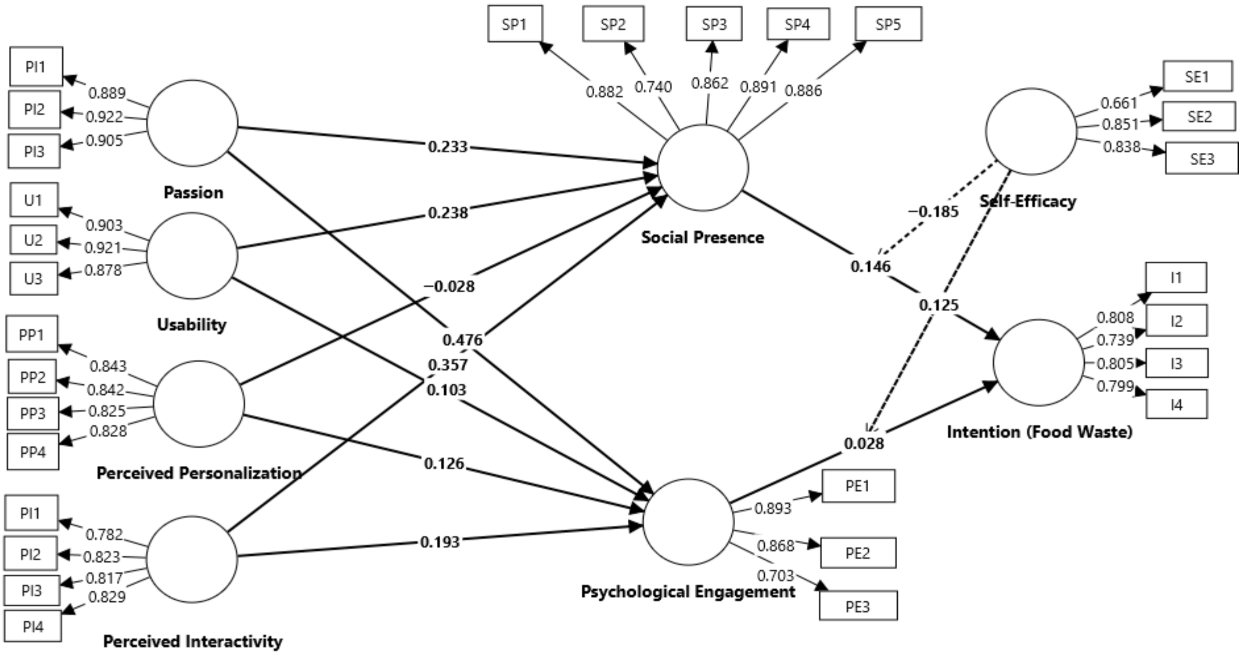

Figure 2. Measurement model.

Table 3. Discriminate validity.

	I	P	PI	PP	PE	SE	SP	U
Intentions to Reduce Food Waste	0.788							
Passion	0.239	0.906						
Perceived Interactivity	0.376	0.658	0.813					
Perceived Personalization	0.332	0.658	0.781	0.834				
Psychological Engagement	0.209	0.758	0.677	0.664	0.826			
Self-Efficacy	0.396	0.303	0.348	0.400	0.361	0.788		
Social Presence	0.219	0.617	0.654	0.576	0.637	0.243	0.854	
Usability	0.204	0.703	0.696	0.721	0.663	0.311	0.630	0.901
HTMT								
Passion	0.267							
Perceived Interactivity	0.456	0.763						
Perceived Personalization	0.402	0.751	0.832					
Psychological Engagement	0.295	0.806	0.825	0.790				
Self-Efficacy	0.528	0.384	0.451	0.512	0.489			
Social Presence	0.244	0.687	0.750	0.652	0.772	0.312		
Usability	0.229	0.787	0.811	0.825	0.781	0.394	0.700	

4. Results

4.1. Structural Model

The coefficient of determination (R^2 value) assesses how much of the variance in the data is explained by the model [131]. For example, in consumer behaviors, R^2 values of 0.20 indicate solid predictive capabilities [132]. The PLS-SEM structural estimation model was initiated with 5000 resamples. In the current study, the model's overall explanatory power (R^2) indicated that it accounted for 51.1%, 64.4%, and 20.1% of social presence, psychological engagement, and behavioral intention to reduce food waste (Figure 3).

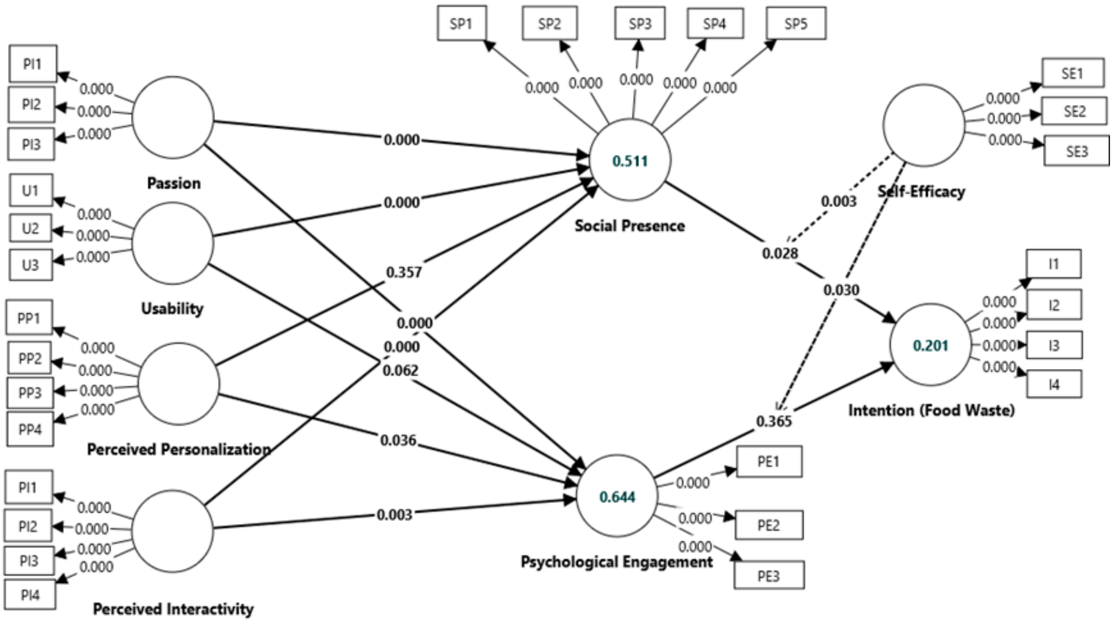

Figure 3. Structural model.

To evaluate the hypothetical model, the researchers used PLS-SEM with the Bootstrap 5000 sampling technique recommended by [132]. Table 4 shows the hypothetical relationships. According to the PLS-SEM results, both passion (β = 0.233; t-value = 3.365; *p*-value = 0.001) and usability (β = 0.238; t-value = 3.354; *p*-value 0.001) have a significant impact on social influence, thus supporting H1 and H3. In terms of divergence, usability (β = 0.103; t-value = 1.541; *p*-value = 0.123) and perceived personalization (β = −0.028; t-value = 0.365; *p*-value = 0.715) do not have a significant effect on psychological engagement, which leads to the rejection of H4 and H5. Additionally, perceived interactivity (β = 0.357; t-value = 4.821; *p*-value = 0.000) significantly affects social presence and psychological engagement (β = 0.193; t-value = 2.717; *p*-value = 0.007); therefore, H7 and H8 are accepted. Conversely, social presence (β = 0.146; t-value = 1.914; *p*-value = 0.056) and psychological engagement (β = 0.028; t-value = 0.346; *p*-value = 0.729) do not significantly affect the intention to reduce food waste, leading to the rejection of H9 and H10.

The indirect effects through social presence and psychological engagement (H11 and H12) were all rejected because the paths showed insignificant values. Moreover, self-efficacy interacts with social presence (β = 0.185; t-value = 2.800; *p*-value = 0.005) and significantly influences the intention to reduce food waste, supporting H13(a), while it does not significantly influence psychological commitment (β = 0.125; t-value = 1.876; *p*-value = 0.061), leading to the rejection of H13(b).

4.2. Multigroup Analysis

Using a multigroup analysis (MGA), this study examined the influences of variables on Generation Y and Generation Z. According to Fang, W. T., Ng, E., Wang, C. M., and Hsu, M. L. [133], the analysis of different groups is carried out using four methods: the parametric approach, which is known for its leniency; followed by the permutation and confidence-based approaches, which are more rigorous; and finally, the most comprehensive method, Henseler's multigroup approach. Henseler, J., C.M. Ringle, and M. Sarstedt [130] further developed this method by introducing PLS-MGA (multigroup analysis). This method identifies significant differences between groups when *p*-values are below 0.05 or above 0.95.

Table 4. Hypothetical relationships.

Hypothesis	Relationship	Beta	T-Value	p-Value	Status
H1	Passion → Social Presence	0.233	3.365	0.001	Accepted
H2	Passion → Psychological Engagement	0.476	7.463	0.000	Accepted
H3	Usability → Social Presence	0.238	3.354	0.001	Accepted
H4	Usability → Psychological Engagement	0.103	1.541	0.123	Rejected
H5	Perceived Personalization → Social Presence	−0.028	0.365	0.715	Rejected
H6	Perceived Personalization → Psychological Engagement	0.126	1.798	0.072	Rejected
H7	Perceived Interactivity → Social Presence	0.357	4.821	0.000	Accepted
H8	Perceived Interactivity → Psychological Engagement	0.193	2.717	0.007	Accepted
H9	Social presence → Intentions to reduce food waste	0.146	1.914	0.056	Rejected
H10	Psychological Engagement → Intentions to reduce food waste	0.028	0.346	0.729	Rejected
H11(a)	Passion → Social Presence → Intentions to reduce food waste	0.034	1.473	0.141	Rejected
H11(b)	Usability → Social Presence → Intentions to reduce food waste	0.035	1.796	0.072	Rejected
H11(c)	Perceived Personalization → Social Presence → Intentions to reduce food waste	−0.004	0.322	0.748	Rejected
H11(d)	Perceived Interactivity → Social Presence → Intentions to reduce food waste	0.052	1.744	0.081	Rejected
H12(a)	Passion → Psychological Engagement → Intentions to reduce food waste	0.013	0.341	0.733	Rejected
H12(b)	Usability → Psychological Engagement → Intentions to reduce food waste	0.003	0.289	0.773	Rejected
H12(c)	Perceived Personalization → Psychological Engagement → Intentions to reduce food waste	0.003	0.304	0.761	Rejected
H12(d)	Perceived Interactivity → Psychological Engagement → Intentions to reduce food waste.	0.005	0.316	0.752	Rejected
H13(a)	Self-Efficacy × Social Presence → Intentions to reduce food waste	−0.185	2.800	0.005	Accepted
H13(b)	Self-Efficacy × Psychological Engagement → Intentions to reduce food waste	0.125	1.876	0.061	Rejected

Using percentile bootstrapping, our analysis revealed significant group variances. p-values outside the 5–95% range indicate that group A outperforms group B below 5% and vice versa above 95%. The pathways for each group that were analyzed are listed in Table 5. The outcomes of MGA, as indicated by the p-values, show notable differences between the groups.

Table 5. Generation analysis.

Hypothesis	Relationship	Gen Y	Gen Z	Diff	PLS MGA Value
H1	Passion → Social Presence	0.262	0.131	0.131	0.181
H2	Passion → Psychological Engagement	0.456	0.484	−0.028	0.405
H3	Usability → Social Presence	0.302	0.113	0.189	0.113
H4	Usability → Psychological Engagement	0.174	0.001	0.173	0.118
H5	Perceived Personalization → Social Presence	−0.126	0.199	−0.325	0.013
H6	Perceived Personalization → Psychological Engagement	0.027	0.246	−0.219	0.059
H7	Perceived Interactivity → Social Presence	0.413	0.297	0.116	0.213
H8	Perceived Interactivity → Psychological Engagement	0.261	0.131	0.130	0.178
H9	Social Presence → Intentions	0.184	0.103	0.081	0.328
H10	Psychological Engagement → Intentions	−0.049	0.097	−0.146	0.192
H11(a)	Passion → Social Presence → Intentions	0.048	0.014	0.034	0.200
H11(b)	Usability → Social Presence → Intentions	0.056	0.012	0.044	0.139
H11(c)	Perceived Personalization → Social Presence → Intentions	−0.023	0.021	−0.044	0.136
H11(d)	Perceived Interactivity → Social Presence → Intentions	0.076	0.031	0.045	0.237
H12(a)	Passion → Psychological Engagement → Intentions	−0.022	0.047	−0.069	0.202
H12(b)	Usability → Psychological Engagement → Intentions	−0.009	0.000	−0.009	0.344
H12(c)	Perceived Personalization → Psychological Engagement → Intentions	−0.001	0.024	−0.025	0.248
H12(d)	Perceived Interactivity → Psychological Engagement → Intentions	−0.013	0.013	−0.026	0.224
H13(a)	Self-Efficacy x Social Presence → Intentions	−0.279	−0.062	−0.217	0.089
H13(b)	Self-Efficacy x Psychological Engagement → Intentions	0.214	0.059	0.155	0.132

Regarding generational differences between Gen Y and Gen Z, H5 ($p = 0.013 < 0.05$) showed significant inequality, underscoring that the association between perceived personalization and social presence was stronger in the Generation Y cohort than in the Generation Z cohort. For the remaining hypotheses, our study found no significant differences between Generation Y and Generation Z.

5. Discussion

This study sought to elucidate the intricate relationship between user experience design and behavioral intention for food waste reduction through AI-enabled applications within this comprehensive framework. This study's major addition is the empirical evidence indicating that consumers' intents are not significantly affected by the existence of AI-based features when mediated by social presence or psychological involvement, hence addressing RQ3 through the rejection of the corresponding research question. The findings specifically resulted in the rejection of hypotheses H11(a) through H11(d), which posited that social presence would significantly influence the correlations between each AI component (passion, usability, perceived personalization, and perceived interaction) and the propensity to waste food. Similarly, hypotheses H12(a) to H12(d), which proposed that psychological involvement would mediate the identical correlations, were likewise dismissed.

These findings contradict previous studies that highlighted the significance of affective and cognitive mediators in improving the efficacy of AI-based applications [61–63,110]. Previous research indicated that when users experience social connection or emotional engagement with an application, they are more inclined to convert AI-enhanced experiences into significant behavioral intents, such as minimizing food waste. Nonetheless, the present findings suggest that although users may feel passion or recognize interactivity and personalization within the app, these factors do not inherently lead to elevated intentions to act and deny RQ1, especially when influenced by social presence or psychological involvement. This indicates that customers' intentions concerning food waste may be less affected by app-induced psychological mechanisms than previously thought [38,134]. One perspective is that users' established behavioral habits, external social norms, or perceived worth of the outcome may exert a more significant influence than the emotional or interactive qualities offered by the app. The dismissal of subhypotheses H11 and H12 signifies that the effectiveness of AI-driven food waste applications relies not solely on their engagement or social immersion but also on wider contextual and motivating elements.

Furthermore, passion was determined to exert a positive influence on both social presence and psychological involvement. This indicates that content conveying emotions and motivational messages can enhance user experience; nevertheless, this effect did not substantially alter behavioral intentions. Similarly, usability was positively correlated with social presence, reinforcing the notion that an intuitive, user-friendly interface enhances feelings of connection among individuals. Nevertheless, this did not result in a modification of intention. These distinctions indicate that emotional and usability-based cues can enhance intermediate psychological responses; nevertheless, they cannot independently influence intention without other contextual or incentive factors. Usability has a big effect on social presence, but it does not influence psychological engagement. This means that a smooth and easy-to-use interface does not always lead to profound cognitive or emotional commitment, as previous studies have shown [61,63]. This means that accessibility can make an app seem socially accessible, but it may not automatically make people think, pay attention, or devote themselves emotionally. Psychological involvement probably needs more than just ease of use; it needs information and experiences that emotionally connect with or intellectually challenge the user. So, to increase user involvement, for

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AI-based apps, we need to do more than just make things work well. We need to add more personalized inspiration.

The finding that perceived personalization has minimal impact on social presence or psychological engagement contradicts prevalent research indicating that personalization invariably enhances user experience [51,89]. This finding may stem from researchers perceiving personalization as lacking social significance or emotional engagement when it consists solely of basic recommendations or interface modifications. Users may not perceive that individualized content in food waste applications equates to a socially engaging environment or sufficiently engages them on a personal level to evoke emotional involvement. In such circumstances, personalization may fail to foster a sense of understanding or emotional engagement, hence not stimulating the social or psychological dimensions. While research indicates that perceived interactivity positively influences both social presence and psychological engagement, it validates the preceding research [51]. It facilitates bidirectional communication, enhancing individuals' sense of societal involvement while necessitating greater attention, interest, and emotional commitment from the user. This aligns with a conceptual framework that can significantly influence the future of Human–Computer Interaction (HCI) in a more substantive and pertinent manner. The methodology is referred to as the Human-Engaged Computing (HEC) approach [135].

Although certain AI stimuli effectively enhanced social presence and psychological engagement, this study revealed no significant correlation between these mediators and the intention to mitigate food waste in the context of RQ2 and refutes this assumption. This finding is crucial. Despite users experiencing a sense of social connection or emotional attachment to the application, such feelings do not inherently motivate behavioral change regarding food waste. This contradicts the notion that presence or engagement invariably results in action [62,106]. The findings indicate that more profound motivational factors may govern intention. These elements may not be sufficiently activated by digital connectivity alone. Social presence and psychological engagement alone were insufficient to predict intention; however, they became significant for individuals with strong self-efficacy, justifying [107] social cognitive theory. Extenuating the behavioral and self-efficacy significance on food waste intention of [45], the results suggest that social connection fosters intention alone when users believe they can individually reduce food waste, and psychological involvement promotes behavioral commitment only when users perceive their ability to undertake environmentally beneficial behaviors and address the specifics of RQ4. This discovery elucidates the prior conundrum: why engagement did not result in intention throughout the entire group. It elucidates that participation is significant but solely for individuals who possess self-assurance and robust self-efficacy.

The fact that there is a big age difference in the path between perceived personalization and social presence (H5) supports generational theory by showing that different generations see digital customization in different ways. Generation Y users liked personalization more when it came to social presence, which supports the idea that digital maturity and real-life experiences alter how different generations interact with AI stimuli.

5.1. Theoretical Implications

This work advances the Stimulus–Organism–Response (S-O-R) model and further explores consequences. First, it opposes the idea that using digital apps inevitably promotes environmental behaviors. Passion and interactivity in AI increased psychological engagement and social presence, but they did not predict behavioral intention. The commonly established "engagement–intention" approach may not always apply, especially when targeting intricate behaviors like food waste reduction. This study is further extended by including the psychological notions of social presence and psychological engagement as mediators, along with self-efficacy as a moderator. This moderate mediation concept highlights the significance of individual psychological aspects in influencing digital behavior outcomes. The conclusions authenticate Bandura's Social Cognitive Theory, demonstrating that users' self-efficacy is crucial for converting digital experience into intention. Ultimately, the dismissal of perceived personalization as a significant predictor of engagement contradicts prior research on personalization, indicating that not all forms of algorithmic personalization function uniformly for all users. This introduces new theoretical challenges about the efficacy, effectiveness, and authenticity of personalization in AI-driven systems. This study indicates an obligation to alter our cognitive approach. Rather than only examining forms of user involvement, we must consider frameworks that prioritize empowerment, motivation, and self-regulation in digital sustainability interventions. The age difference in the path between perceived personalization and social presence distinction suggests that S-O-R should be divided by age to properly show how different users are.

5.2. Practical and Managerial Implications

This study provides practical insights for sustainability proponents employing AI to facilitate behavioral change. AI applications need to surpass visually pleasing or engaging designs with functions that reinforce users' self-assurance. This can be accomplished by measures such as progress monitoring, personalized feedback, goal establishment, or real-time impact visualization that strengthen users' confidence in their capacity to minimize food waste.

Since self-efficacy moderates the relationship between engagement and intention, it is imperative to customize app characteristics based on users' psychological preparation. Applications designed for those with poor self-efficacy may incorporate lectures, social validation, or utilize gaming for incentives to enhance competence. The discovery that perceived personalization lacked considerable influence indicates that personalization must transcend mere aesthetic adjustments. There is a need for improvements in human-focused methodologies, including value-based personalization, user-driven customization, and reactive feedback, to enhance applicability and engagement.

Managers need to reconsider the implementation of personalization, potentially transitioning from algorithmic adaptation to value-based or user-driven personalization, which more profoundly engages with consumers. Managers should not rely exclusively on app-based solutions but include them in wider business or community endeavors. Partnerships with food suppliers, waste management firms, or educational organizations can augment reach and influence. In short, managers seeking impact behaviors using AI-based platforms must transition their priority from passive engagement to empowerment and behavioral reinforcement. By integrating obvious approaches, personal assistance, and confidence-enhancing strategies, they may connect digital engagement with sustainable behaviors within actual life.

5.3. Limitations and Future Research Directions

The sample, restricted to Generation Z and Generation Y Lithuanian consumers, limits the generalizability of the research findings, as food waste patterns may differ among earlier generations. This study was conducted within a specific demographic and cultural context, potentially affecting generalizability. Cross-cultural replication is crucial for assessing the robustness of the results. The study may be expanded to include qualitative or observational methodologies, as it is currently restricted to quantitative data collection, which would enhance its comprehensiveness. While self-efficacy emerged as a key moderator, additional moderators such as environmental concern, social norms, or home dynamics could further enhance the model. The implementation of perceived personalization may have concentrated excessively on algorithmic attributes. Future research should investigate human-like personalization and value-based customization.

However, these experiences alone do not make consumers intend to reduce food waste. No data indicated that social presence or psychological engagement could independently predict intention, and none of the mediated paths from AI stimuli to intention were statistically validated. But the moderating role of self-efficacy gave us significant information. The interaction effects demonstrated that when users have high self-efficacy, the beneficial effects of social presence and psychological engagement become important in shaping their intentions. This result reinforces the idea that self-efficacy is a psychological tool that helps digital encounters turn into meaningful behavioral goals. Also, the fact that perceived personalization did not have a substantial effect goes against the widespread belief that algorithmic customization always makes people more interested or willing to act. Conversely, personalization that lacks relevance or authenticity may fail to resonate with individuals in a meaningful manner.

In conclusion, AI-based apps can improve user involvement through emotional and social design, but these experiences need to be backed up by ways to let users believe in their own power to act. To be useful, AI interventions in sustainability need to do more than just look good and be interactive. They also need to build users' confidence, give them power, and prepare them to change their behaviors. These results add to theory by expanding moderated mediation models in digital behavior research and add to practice by showing how important self-efficacy is in creating AI-driven sustainability solutions that really work.

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Institutional Review Board Statement: This study is waived for ethical review as the study was conducted using a fully anonymous online survey by the Kaunas University of Technology (KTU) Internal Ethical Self-Assessment Procedure.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to however, the datasets cannot be publicly shared due to respondents' privacy concerns. Participants were assured that the data would be used solely for research purposes and would not be shared with any third party. Therefore, the data is not publicly available.

Conflicts of Interest: The authors declare no conflicts of interest.

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