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Explaining consumer engagement with deposit-refund systems through the three-component attitude model: A circular economy perspective from hungary

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ABSTRACT

Deposit-refund systems (DRS) are widely recognized as effective instruments of the circular economy, however, their long-term success depends not only on technical design and financial incentives but also on consumer engagement. Empirical research on the psychological drivers of DRS participation remains limited, especially in Central and Eastern Europe, creating a need to understand how attitudes shape behavioral adoption in early-stage systems. This study applies the three-component attitude model, distinguishing cognitive, affective, and conative dimensions, to explain consumer participation in Hungary's newly introduced national DRS, the REpont scheme. Unlike most previous applications, the model was identified inductively from empirical data through exploratory and confirmatory factor analyses, providing a data-driven theoretical contribution to behavior research. A large-scale survey ($n = 2665$) was conducted and analyzed using partial least squares structural equation modeling (PLS-SEM). The findings indicate that affective and conative attitudes are strong predictors of system use, while cognitive evaluations exert a moderate but significant effect. For the latter, however, demographic and cluster analyses revealed subgroups (urban, highly educated) with reduced usage despite higher awareness. Emotional commitment strengthens favorable evaluations, which in turn encourage behavioral intentions and routines, confirming the sequential pathway from affect to cognition to conation. From a theoretical perspective, the study extends the attitude model to a novel circular economy context, while from a policy and managerial perspective, it highlights that addressing infrastructural barriers and contextual challenges and strengthening emotional engagement are essential to ensure the long-term effectiveness of DRS.

1. Introduction

The transition toward a circular economy has placed increasing emphasis on reducing packaging waste and promoting sustainable consumption. Beverage packaging constitutes a non-trivial share of municipal solid waste and represents a critical challenge for both environmental policy and waste management (Onel and Mukherjee, 2015; van Birgelen et al., 2009). Deposit-refund systems (DRS), also known as deposit-return systems, have therefore emerged as one of the most effective policy tools to achieve high recovery and recycling rates for beverage containers, offering consumers a direct economic incentive to return used packaging (Numata, 2016). By combining financial motivation with structured return infrastructure, DRS have been implemented in many countries worldwide, especially in the European Union, and have generally been associated with high collection rates (Phipps et al., 2024; Reshetnikova et al., 2025).

Despite their technical effectiveness, the long-term success of DRS depends on public acceptance and sustained consumer engagement. Previous research has highlighted several key factors influencing consumer participation in DRS. Martinho et al. (2024) emphasized the role of economic incentives in motivating return behavior. Oke et al. (2020) demonstrated that the physical accessibility and convenience of return points significantly determine participation levels. In addition, Phipps et al. (2024) identified system design and operational transparency as critical drivers of sustained engagement. However, growing evidence suggests that these external factors alone cannot fully explain usage patterns. For instance, Roca et al. (2020) showed that detailed technical information or operational shortcomings may even reduce willingness to

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participate, highlighting the importance of psychological and attitudinal factors in shaping behavior. In contrast, broader research on pro-environmental consumer behavior has emphasized the role of attitudes, typically conceptualized as multidimensional constructs (Breckler, 1984; Fraj and Martinez, 2007).

Although the literature on recycling and pro-environmental practices is expanding, empirical applications of psychological attitude components to DRS remain limited, particularly in Central and Eastern Europe. Existing studies (Nameghi and Shadi, 2013; Widodo and Wahid, 2018) mainly focus on economic incentives and infrastructural design, while the multidimensional role of attitudes in shaping routine participation and behavioral consistency has received limited attention. This study addresses this gap by investigating consumer participation in Hungary's newly launched REpont system, which was introduced in 2024 and is operated by MOHU (MOL Hulladékgazdálkodási Zrt.), under a concession model. The system currently covers single-use plastic, metal, and glass beverage containers (0.1–3 liters) that are marked with the official "returnable" label. A 50 HUF deposit fee is charged on each eligible unit, refundable through an expanding network of reverse vending machines (RVMs) installed primarily in larger retail outlets (e.g., supermarkets), while smaller retailers may participate through manual collection. Compared with the well-established Northern-European systems (Picuno et al., 2025), the Hungarian DRS differs in three key aspects: (1) it is newly introduced and still in a transitional phase (e.g., limited RVM coverage and public learning curve), (2) it relies on a centralized, concession-based operator rather than an industry-led consortium, and (3) its deposit value and product scope are relatively narrow at this stage. These structural differences make Hungary an especially relevant context for examining how consumers form psychological responses to a novel circular mechanism that requires behavioral adaptation.

This study followed an exploratory research design aimed at identifying the key psychological dimensions underlying consumer participation in DRS. The questionnaire was intentionally designed to include items that could be interpreted within several well-established behavioral frameworks, such as the Theory of Planned Behavior (TPB), the Norm Activation Model (NAM), and the Value–Belief–Norm (VBN) theory. However, the theoretical alignment was not predetermined; rather, the selection of the explanatory model emerged from the data structure identified through exploratory and confirmatory factor analyses. Based on these empirical results, the three-component attitude model, developed by Breckler (1984), was found to best capture the latent attitudinal dimensions revealed by the analysis. While affective factors (such as pride or moral satisfaction) and conative factors (e.g., habits or intentions) are known to predict sustainable behavior, their role in explaining routine participation in DRS is still underexplored. Moreover, the cognitive dimension, related to perceived usefulness and knowledge of the system, may exert complex or even contradictory effects, particularly in contexts where operational issues reduce consumer trust or convenience (Roca et al., 2022, 2020).

The contributions of this study are threefold. First, it advances theory by empirically identifying and validating the suitability of the three-component attitude model in the context of DRS, demonstrating its explanatory power for circular economy practices. Second, it provides robust empirical evidence from a large-scale, nationally representative survey ($n = 2665$), showing how cognitive, affective, and conative attitudes interact to predict actual system usage. Third, it offers practical insights for policymakers and system operators by identifying demographic and contextual factors, such as education and urban infrastructure, that condition consumer engagement, thereby informing more effective system design and communication strategies, supporting the transition toward a circular economy.

This study aims to fill the above-mentioned gaps by empirically identifying the key psychological dimensions that drive consumer participation in Hungary's newly introduced REpont DRS. Following an exploratory design, the analysis revealed a latent structure consistent with the three-component attitude model, which was used to interpret the results. This approach allows for a data-driven examination of how attitudes shape routine participation in a circular system. Thus, the objective of the study is twofold: first, to identify the underlying psychological dimensions that explain consumer participation in the REpont DRS; and second, to interpret these dimensions within a circular economy framework, drawing on the empirically revealed three-component attitude model. To address these objectives, the remainder of the paper is structured as follows. Section 2 reviews the literature on DRS and introduces the theoretical foundations of the three-component attitude model. Section 3 describes data collection, survey design, and methodological approach. Section 4 presents empirical results, while Section 5 discusses their implications for theory and practice, outlining limitations and directions for future research. Finally, Section 6 concludes by summarizing the main contributions and key messages of the study.

2. Literature review

2.1. Theoretical background

Research on pro-environmental behavior has long emphasized the role of psychological and attitudinal constructs in shaping consumer decision-making. Among the most influential frameworks is the Theory of Planned Behavior (TPB), which conceptualizes intention as the central predictor of behavior, driven by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). While TPB has been widely applied to recycling, waste reduction, and sustainable purchasing, researchers increasingly argue that a deeper and more complex understanding of attitudes themselves is required (Park and Ha, 2014; Valle et al., 2005). The multidimensional attitude theory, also referred to as the three-component attitude model, conceptualizes attitudes as a combination of cognitive (belief-based), affective (emotion-based), and conative (behavioral intention-based) dimensions (Breckler, 1984). Cognitive attitudes refer to beliefs and knowledge about a behavior; affective attitudes capture emotions and feelings, while conative attitudes represent intentions and habitual patterns of action. Recent applications of this multidimensional approach in sustainability and recycling contexts have been shown to improve predictive power in explaining ecological consumer practices (Best and Mayerl, 2013; Nameghi and Shadi, 2013; Widodo and Wahid, 2018).

Several authors have further highlighted that affective commitment and habitual conative elements often outweigh purely cognitive evaluations when predicting recycling or pro-environmental routines (Ari and Yilmaz, 2023; Barr, 2007). Other authors extended this view to cultural contexts. McCarty and Shrum (2001) showed that individualism and collectivism shape which of the attitudinal components dominate recycling behavior. Best and Mayerl (2013) also demonstrated that cognitive evaluations of environmental values must be paired with affective commitment and habitual routines to translate into actual behavioral change. In addition, at the same time, the literature suggests that combining attitude models with broader behavioral theories enhances explanatory potential. Studies integrating the three-component model with frameworks, such as TPB or NAM, demonstrate that attitudinal processes interact with social and contextual drivers, producing more comprehensive explanations of recycling participation (Mosler et al., 2008; Valle et al., 2005). In line with this, past behavior and subjective norms influence pro-environmental decisions primarily through their impact on the affective and conative dimensions of attitudes (Biswas et al., 2000).

More recent research, however, emphasizes that traditional TPB may underestimate the affective, habitual, and experiential components of circular behavior. The extended TPB incorporates additional constructs such as moral norms, anticipated emotions, and affective attitudes, thereby improving its predictive capability in environmental and recycling contexts (Ajzen, 2020; Klöckner, 2013). Furthermore, Ogiemwonyi (2024) revisited the determinants of green behavior and emphasized that affective and moral dimensions play an increasingly central role in translating environmental beliefs into consistent behavioral patterns. Similarly, Ogiemwonyi and Jan (2023) demonstrated that moral obligation and ethical beliefs strengthen the predictive power of pro-environmental attitudes, suggesting that affective and normative elements complement cognitive evaluations in shaping behavior. These findings align with the present study's conceptualization of cognitive, affective, and conative dimensions as interconnected predictors of participation in circular practices.

In parallel, the Value–Belief–Norm (VBN) theory (Stern et al., 1999) provides a moral and value-based extension to cognitive-behavioral models. The VBN framework posits that individuals' core value orientations—altruistic, biospheric, and egoistic—influence environmental beliefs, which, in turn, activate personal moral norms guiding pro-environmental behavior (Hansla et al., 2008). Integrating the VBN perspective allows for capturing moral obligation and value-driven motivations that often underpin consumers' recycling and circular participation (Al Mamun et al., 2022, 2024). Furthermore, from a circular economy perspective, Ogiemwonyi (2025) highlighted the need to understand consumer behavior as a key driver of system-level transitions, arguing that emotional and value-based engagement are essential for fostering sustained participation in circular systems such as the investigated DRS.

The current research extends this theoretical dialogue by empirically testing the multidimensional structure of consumer attitudes within an operational DRS context. Such integrative approaches are particularly relevant in the case of DRS, where participation depends not only on economic incentives and infrastructural availability but also on how consumers perceive, evaluate, and routinely engage with the system. By adopting this theoretical background, the present study positions the three-component attitude model as a robust framework for investigating consumer participation in the Hungarian REpont DRS, identified through exploratory analysis as the most suitable explanatory approach. This model makes it possible to move beyond instrumental predictors and to systematically capture the interplay among knowledge, emotions, and behavioral intentions in shaping sustainable consumption practices.

2.2. Sustainability and attitude model

While the three-component attitude model has been widely applied to general pro-environmental practices, its explicit use in the context of DRS remains limited. Most existing studies focus primarily on external, instrumental determinants of participation, such as financial incentives and infrastructural availability, rather than on internalized attitudinal processes (Borucka and Grzelak, 2025; Konstantoglou et al., 2023). This has created a research gap, as the effectiveness and long-term acceptance of DRS depend not only on system design but also on how consumers perceive, evaluate and routinely engage with the scheme. Current empirical evidence suggests that financial rewards, the physical accessibility of RVMs, and the quality of system-related communication significantly influence public participation (Martinho et al., 2024). However, detailed technical information on system operation has in some cases been associated with negative evaluations and reduced willingness to participate (Roca et al., 2020). Although several studies have highlighted the influence of moral motivations or the role of social norms in DRS adoption (Konstantoglou et al., 2023), these factors are often examined outside the formal framework of the classical attitude model, and structural relationships among attitudinal components are rarely assessed. The conative underpinnings of DRS participation, i.e., habits, routines, or unconscious behavioral patterns, remain largely unexplored, despite evidence that they are among the most influential predictors of other forms of environmental behavior (Fraj and Martinez, 2007).

In environmental psychology, the three-component model has been repeatedly validated for recycling, waste reduction, and sustainable consumption (Fraj and Martinez, 2007; Nameghi and Shadi, 2013; Widodo and Wahid, 2018). Escario et al. (2020) recently confirmed that linking environmental attitudes with perceived system effectiveness is crucial in predicting waste-reduction practices. In the context of DRS, however, research has mostly emphasized instrumental factors. For example, Martinho et al. (2024) demonstrated that system design and convenience strongly predict participation, while Oke et al. (2020) highlighted consumer concerns about accessibility and technical issues. Similarly, Roca et al. (2020) found that excessive technical information or operational problems may reduce participation, showing that cognitive evaluations of the system can have counterintuitive effects. These findings suggest that relying exclusively on extrinsic determinants overlooks the role of internalized attitudes in shaping routine engagement.

The relevance of affective and conative components has been indirectly acknowledged in the literature. Konstantoglou et al. (2023) showed that moral considerations and perceived social norms significantly influence acceptance of DRS, while Phipps et al. (2024) identified behavioral intentions as strong predictors of participation. Taken together, these findings suggest that while extrinsic determinants remain important, internalized attitudes, and particularly affective and conative dimensions, are essential for explaining routine engagement in DRS. Thus, in the context of the three-component model, this implies that the affective dimension (emotional responses toward the system) and the conative dimension (behavioral intentions, habits, and routines) can be expected to exert a direct and positive influence on participation. In the present study, participation is conceptualized as the regular and consistent use of the REpont system, reflecting behavioral adoption rather than the absolute number of returns.

Hypothesis 1. *More positive attitudes toward the REpont system are associated with greater behavioral integration, reflected in the regular and consistent use of the system.*

The cognitive attitude component reflects an individual's knowledge and perceived usefulness of the system. Theoretically, greater perceived benefits should increase the willingness to use the system (Fraj and Martinez, 2007; Widodo and Wahid, 2018). However, previous findings indicate that, under certain operational conditions, the cognitive dimension may have a counterintuitive effect: negative experiences and knowledge (e.g., technical errors, cumbersome redemption processes, or insufficient incentives) can diminish the perceived value of the system. This suggests that, when system shortcomings are salient, more knowledge may translate into lower engagement. This is consistent with broader evidence showing that environmental knowledge alone is a weak predictor of actual behavior (Kollmuss and Agyeman, 2002; Steg and Vlek, 2009), and that contextual or technical barriers can strongly attenuate the knowledge–behavior link (Guagnano et al., 1995; Schultz and Oskamp, 1996).

In line with this, more detailed awareness of system shortcomings may even translate into lower engagement, as also observed in waste-separation practices where cognitive factors were overshadowed by infrastructural and social conditions (Knickmeyer, 2020). Furthermore, within this framework, the affective emotions associated with a behavior often emerge as stronger predictors of behavioral intentions compared to purely cognitive evaluations (Ajzen and Fishbein, 2000). Empirical studies confirm that positive emotions such as pride, satisfaction, and enjoyment foster stronger pro-environmental intentions than cognitive beliefs alone (Han and Kim, 2010; Lee et al., 2010). Moreover, previous research suggests that affective attitudes often play a more decisive role than cognitive evaluations in shaping habitual and emotionally reinforced environmental behaviors (Ari and Yilmaz, 2023; Best and Mayerl, 2013). In the case of the Hungarian REpont system, where behavioral adoption is still developing, it is therefore important to examine whether emotional attachment and positive feelings toward the system outweigh rational knowledge in predicting participation. Moreover, as the literature states (AlSaleh and Thakur, 2019; Langenbach et al., 2020), consumers' rational evaluations (cognitive attitudes) may be constrained by operational difficulties and limited user experience, potentially weakening their direct influence on participation compared with affective and conative components.

Hypothesis 2. *Affective attitudes have a stronger positive effect on consumers' intentions to participate in the REpont system than cognitive attitudes.*

Hypothesis 3. *Cognitive attitudes have a weaker positive effect on REpont system use, due to the system's initial operational challenges and limited user experience.*

The sequential relationship between affective, cognitive and conative dimensions has been widely discussed in attitude research. Specifically, cognitive evaluations, such as knowledge about the environmental benefits of a system, can strengthen affective responses, which in turn reinforce behavioral intentions. Recent applications of the model in pro-environmental and sustainability domains provide evidence that affective attitudes often mediate the path from cognition to behavior (Han, 2020; Tang et al., 2022). For instance, Chang and Hsiao (2025) found that green perceived value fully mediated the positive relationship between environmental cognition and low-carbon tourism intentions, demonstrating a clear cognitive-affective-conative pathway. Similarly, Tang et al. (2022) found that affective components significantly mediated the influence of cognitive factors on pro-environmental tourist behavior, reinforcing the model's validity in environmental behavior research. Moreover, Wiśniewska et al. (2025) reported that awareness and knowledge (cognitive) predicted emotional concern (affective), which then influenced consumer attitudes toward sustainable practices, underlining the sequential structure of the attitude model. In the context of the REpont system, this process is particularly relevant because consumers are still developing familiarity and trust in the mechanism. Rational understanding of environmental benefits (cognitive) may not immediately lead to participation but can first evoke emotional responses such as satisfaction or moral pride (affective), which subsequently motivate consistent engagement (conative). In the case of a newly introduced DRS, positive emotional responses (affective) can prime favorable knowledge and usefulness evaluations (cognitive), thereby strengthening behavioral intentions and routines (conative).

Hypothesis 4. *Cognitive attitudes mediate the influence of affective attitudes on consumers' conative responses (intentions and actual use) of the REpont System.*

Overall, the proposed hypotheses aim to test whether the affective and conative dimensions align with the established positive link between favorable attitudes and pro-environmental behavior, and whether the cognitive dimension diverges from this pattern under the specific contextual constraints of the REpont scheme.

2.3. Sociodemographic factors in recycling and DRS participation

Previous research has shown that sociodemographic characteristics marginally influence consumers' environmental and recycling behaviors. Age and gender differences often reflect varying socialization patterns and environmental awareness levels, with women and younger individuals generally showing stronger pro-environmental attitudes (Diamantopoulos et al., 2003; Miafodzyeva and Brandt, 2013). Educational attainment and income are also positively associated with recycling participation and willingness to engage in circular schemes, as they enhance access to information, awareness, and perceived behavioral control (Barr, 2007; Oke et al., 2020; Vicente and Reis, 2008). Urban–rural disparities have also been examined, with residents of larger cities typically showing higher participation rates due to greater system accessibility and convenience (Ile et al., 2025; Sidique et al., 2010). These demographic factors are expected to moderate behavioral engagement by shaping both knowledge and emotional commitment toward recycling routines.

Beyond individual sociodemographic traits, contextual and infrastructural inequalities also play a major role in explaining variation in recycling engagement. Studies demonstrate that access to collection facilities, proximity to return points, and exposure to environmental communication campaigns often interact with education and income, amplifying behavioral differences among social groups (Geiger et al., 2018; Gyrd-Jones and Kornum, 2013). Moreover, cross-country research on DRS indicates that early adoption tends to cluster among younger, urban, and higher-educated consumers, characterized by stronger environmental identities (Konstantoglou et al., 2023; Kremel, 2024; Stoeva and Alriksson, 2017). Accordingly, these demographic and contextual variables are considered as potential moderators of the attitudinal–behavioral relationships within the REpont system.

3. Materials and methods

3.1. Presentation of the questionnaire and sample

The analysis was based on a structured questionnaire developed in accordance with the theoretical foundations of previous research on environmental attitudes and consumer behavior (Breckler, 1984; Fraj and Martinez, 2007; Nameghi and Shadi, 2013; Widodo and Wahid, 2018). The items were designed to capture respondents' emotional responses, knowledge and beliefs, as well as habitual and intentional behaviors related to the REpont redemption scheme. Data collection was carried out between 24 September and 24 December 2024. The questionnaire was disseminated in social media groups with at least 1000 members, specifically targeting settlement- and region-specific communities to ensure a diverse and geographically balanced sample across the country. This recruitment strategy aimed to achieve a socially diverse sample, with explicit attention to variation in gender, age, and place of residence. Participation in the survey was entirely voluntary, and all participants were informed, prior to starting the questionnaire, about the study's purpose, the procedures for data handling, and the assurance of anonymity. Throughout the process, internationally recognized methodological standards for social media-based research were followed (Fricker, 2008; Kosinski et al., 2015). The questionnaire contains a variety of item types, including yes/no questions, open-ended demographic items, and Likert-scale (1–5) statements designed to measure attitudinal, behavioral, and contextual aspects of recycling and REpont system use, as well as perceived usefulness, ease of use, satisfaction, and financial motivation.

A total of 3088 individuals completed the questionnaire. To ensure data quality, four exclusion criteria were applied: (1) incomplete responses were removed; (2) straight-lining was identified and excluded, i.e., respondents who provided the same answer across all items; (3) respondents who gave deliberately nonsensical answers to open-ended demographic questions (e.g., random strings or unrealistic age); and (4) responses submitted in an unrealistically short completion time, below the predefined minimum threshold for valid participation, were also removed, as these were considered to indicate insufficient engagement with the questionnaire. After data cleaning based on the predefined quality criteria, the final sample contains 2665 valid responses.

In the case of online data collection based on voluntary participation, voluntary-response bias is a well-known methodological challenge for which, according to the literature (Steinmetz et al., 2009; Vaske et al., 2011), no comprehensive solution has yet been developed. However, several studies have shown that demographic weighting can improve the fit between the sample and population proportions, thereby increasing the generalizability of the results (Loosveldt and Sonck, 2008). In international research practice, this approach is an accepted and widely used alternative to probability sampling, especially with the growing prevalence of online surveys and the data collection constraints following the COVID-19 pandemic, when conducting face-to-face interviews is often no longer a feasible option. Thus, to improve representativeness, the sample was post-weighted by gender, age, education, and region, using population distribution data published by the Hungarian Central Statistical Office (HCSO) in 2024 (see Table 1). The weighting procedure was performed using the R package anesrake, which implements the raking post-stratification method (DeBell and Krosnick, 2009). This step was undertaken to mitigate potential sampling bias arising from the non-probability nature of recruitment via online platforms.

3.2. Methods and models used

The data were analyzed using structural equation modeling (SEM) implemented through variance-based partial least squares (PLS-SEM). This method is particularly appropriate for examining complex attitudinal models in which the constructs are measured with Likert-scale indicators, and where the assumption of multivariate normality cannot be guaranteed (Haenlein and Kaplan, 2004; Henseler et al., 2015). Moreover, PLS-SEM is well suited for predictive modelling and theory development in relatively underexplored domains, such as consumer engagement with DRS (Chin et al., 2020; Lowry and Gaskin, 2014; Pereira et al., 2024).

Two complementary models were estimated in this research. First, a measurement model was applied, in which exploratory and confirmatory factor analyses were used to identify the main components and assign the corresponding questionnaire items to these latent constructs. Before conducting the factor analyses, the dataset was examined for common method bias and statistical adequacy. The Harman's single-factor test revealed that a single factor accounted for only 40.4 % of the total variance, well below the 50 % threshold commonly used to indicate bias (Podsakoff et al., 2003). Furthermore, the marker-variable technique (Simmering et al., 2015) using items theoretically unrelated to the core constructs confirmed that common method bias was not a concern, as its correlations with the substantive items ranged between 0.14 and 0.49, with most values below 0.30. The suitability of the data for factor analysis was also confirmed by the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, which reached an overall value of 0.923, classified as "excellent" (Kaiser, 1974).

In addition, Bartlett's test of sphericity indicated that the correlation matrix significantly differed from the identity matrix ($\chi^2(66) = 2.0 \times 10^4$, $p < 0.001$) (Bartlett, 1954). Moreover, the determinant of the correlation matrix was 0.007642, confirming the absence of multicollinearity among variables. All individual MSA values exceeded 0.87, indicating that each variable was suitable for inclusion in the analysis. Communalities ranged between 0.47 and 0.82, suggesting that a substantial proportion of the variance in each item was explained by the extracted factors. Residual correlations were low (absolute values below 0.20), providing further evidence for the adequacy of the factor solution. Internal consistency was verified using Cronbach's alpha, which reached 0.889, indicating high reliability. The applied diagnostics (KMO, Bartlett's test, determinant of the correlation matrix, and Cronbach's alpha) follow established methodological standards for assessing data suitability and reliability in exploratory factor analysis (Field, 2024; Hair et al., 2019).

Second, a structural model was specified to map the hypothesized relationships between these constructs, allowing for the assessment of both the strength and statistical significance of the paths linking latent variables. The measurement models followed a reflective specification, meaning that the observed variables (indicators) were expected to be highly correlated as they represent manifestations of the same underlying construct, in line with recommendations in the literature (Hair, 2014; Petter et al., 2007). Factor analysis confirmed the robustness of the three-dimensional attitude model, encompassing emotional attachment to the REpont system (affective), knowledge and beliefs (cognitive), and behavioral intentions and habitual engagement (conative) (Breckler, 1984; Fraj and Martinez, 2007).

Table 1
Distribution of the post-weighted sample.

Variable	Sample distribution	Hungarian distribution
Gender		
Male	61.94 %	47.57 %
Female	38.06 %	52.43 %
Age category		
18–29	29.11 %	16.04 %
30–39	12.87 %	15.68 %
40–59	43.02 %	36.29 %
60+	15.00 %	31.98 %
Place of residence (region)		
Central Hungary	33.57 %	31.50 %
Central Transdanubia	13.80 %	11.03 %
Western Transdanubia	4.65 %	10.24 %
Southern Transdanubia	5.10 %	8.89 %
Northern Hungary	21.98 %	11.30 %
Northern Great Plain	5.44 %	14.59 %
Southern Great Plain	15.45 %	12.44 %
Highest level of education		
Primary	7.01 %	17.07 %
Secondary	54.99 %	56.68 %
Tertiary	38.00 %	26.25 %

Note: Own data collection post-weighted using the data published by the Hungarian Central Statistical Office (2024).

3.3. Exploratory factor analysis and item reduction

The aim of the study was to identify the underlying dimensions represented by the items in the questionnaire and to develop a well-interpretable, theoretically grounded model. Due to the exploratory nature of the research, the initial large set of variables (36 items) was subjected to an exploratory factor analysis (EFA). The purpose of this method is to identify the latent factors that explain respondents' behavior based on the correlation structure among the variables (Bartlett, 1954; Field, 2024; Kaiser, 1974). The number of factors were determined based on several criteria: the Kaiser criterion (eigenvalue > 1) and the visual inspection of Cattell's scree plot. The breakpoint occurred after the third factor, which justified the retention of three distinct dimensions. Together, these three factors explained a significant portion of the total variance and, based on the items associated with them, fit well within the theoretical framework of the three-component attitude model (cognitive–affective–conative). The exploratory factor analysis and the scree plot are presented in the Appendix (Table A1 and Fig. A1).

A varimax rotation was applied to simplify the factor structure and enhance interpretability. Item reduction was performed iteratively by removing items with low factor loadings or cross-loadings. A threshold value of 0.50 was applied for the first two factors and 0.30 for the third factor, given its behavioral nature and expected heterogeneity. According to the literature, factor loadings between 0.30 and 0.40 are also interpretable for large samples ($N > 300$) if they are theoretically grounded and consistently related to the factor (Tabachnick et al., 2007). Since the sample size of the present study exceeded 2600, the use of the 0.30 threshold was statistically and theoretically justified. As a result of this procedure, 12 items remained, each of which clearly belonged to a single factor and showed a strong relationship with the respective dimensions (the items excluded during item reduction from the model are presented in Table A2 in the Appendix). The rotated three-factor solution explained 61.6 % of the total variance (Factor 1 – 30.6 %, Factor 2 – 22.7 %, Factor 3 – 8.3 %). Given the number of items (12), this level of explained variance can be considered satisfactory. The factor matrix is presented in Table 2.

The exploratory factor analysis indicated a three-factor solution corresponding to the cognitive, affective, and conative components. This outcome guided the subsequent theoretical interpretation, leading to the adoption of the three-component attitude model as the most empirically supported framework among several theoretically plausible

Table 2
Factor structure of the attitude-related variables.

Construct	Variables	Literature	Factor 1 (explained variance: 30.6 %)	Factor 2 (explained variance: 22.7 %)	Factor 3 (explained variance: 8.3 %)
Cognitive component	I find the REpont system user-friendly	Ajzen, 2020; Han and Kim, 2010	0.815	0.212	0.157
	Using the REpont system was simple and convenient	Ajzen, 2020; Han and Kim, 2010	0.785	0.233	0.123
	Using the REpont system makes recycling easier for me	Fraj and Martinez, 2007; Ajzen, 2020; Han and Kim, 2010	0.746	0.190	0.150
	Using the REpont system is a good solution for managing bottle returns	Nameghi and Shadi, 2013; Fraj and Martinez, 2007	0.718	0.278	0.277
Affective component	I consider the REpont system useful	Nameghi and Shadi, 2013; Ajzen, 2020	0.733	0.334	0.158
	I feel good about participating in recycling	Nameghi and Shadi, 2013; Ajzen, 2020	0.215	0.819	0.102
	Recycling is an important value for me	Nameghi and Shadi, 2013; Hansla et al., 2008	0.303	0.811	0.145
	I am proud to contribute to recycling	Nameghi and Shadi, 2013; Hansla et al., 2008	0.186	0.746	0.148
Conative compnent	I would use the REpont system even without financial incentives	Fraj and Martinez, 2007; Phipps et al., 2024	0.424	0.338	0.501
	I am willing to change my daily habits to use the REpont system	Nameghi and Shadi, 2013, Fraj and Martinez, 2007; Han and Kim, 2010	0.447	0.421	0.465
	I will download and use the REpont application	Nameghi and Shadi, 2013, Fraj and Martinez, 2007; Han and Kim, 2010	0.331	0.193	0.460
	I will regularly use the REpont system	Nameghi and Shadi, 2013; Fraj and Martinez, 2007; Ajzen, 2020	0.350	0.426	0.318

alternatives. Based on the variables with the highest loadings, the identified factors correspond to the following components: (1) *Factor 1 – Cognitive elements*: I find the REpont system user-friendly; Using the REpont system was simple and convenient; Using the REpont system makes recycling easier for me; Using the REpont system is a good solution for managing bottle returns; I consider the REpont system useful. (2) *Factor 2 – Affective elements*: I feel good about participating in recycling; Recycling is an important value for me; I am proud to contribute to recycling. (3) *Factor 3 – Conative elements*: I would use the REpont system even without financial incentives; I am willing to change my daily habits to use the REpont system; I will download and use the REpont application; I will regularly use the REpont system.

Selective collection of bottles is not limited to the REpont system; bottles can also be collected in selective bins available everywhere (without cash refund). The analysis focuses on the extent of REpont system use, which is measured by the question “How regularly do you use the REpont system to return bottles?” (1 = *I do not use it*, 5 = *I collect and return every bottle I purchase*). This measure reflects the degree to which respondents integrate the use of the REpont system into their everyday routines, indicating how firmly the behavior has become a stable and habitual part of environmentally responsible practices. The base model structure reflecting these components is presented in Fig. 1.

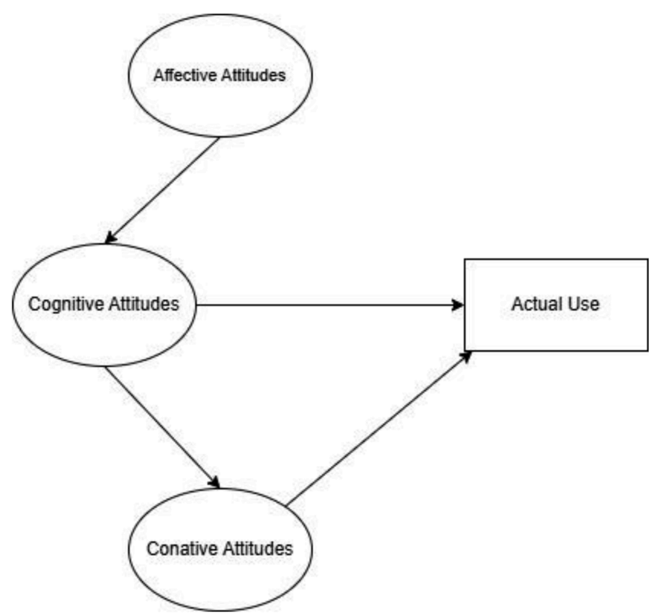

Fig. 1. Conceptual framework based on the three-component (multidimensional) attitude model.

3.4. Demographic analysis

To examine differences in REpont system usage across demographic groups, a one-way analysis of variance (ANOVA) was applied to test whether the mean frequency of system use varied significantly by gender, age, education, income level, settlement type, and region. When significant effects were found, Tukey’s HSD post-hoc tests were performed to identify which specific groups differed (Field, 2024).

To complement these univariate tests and capture potential interactions among demographic variables, k-means cluster analyses were conducted. This exploratory, multivariate approach allows for identifying groups of respondents with similar demographic profiles that may jointly influence usage behavior. The primary segmentation was based on settlement type and education level, the two variables that showed significant effects in the ANOVA. Additional robustness checks were performed using alternative demographic combinations (e.g., age, income, and education). The number of clusters ($k = 3$) was selected based on interpretability and model stability. ANOVA and Bonferroni post-hoc tests were then used to assess significant differences in REpont usage across clusters (Hair et al., 2019).

3.5. Validation of the PLS-SEM model

In the PLS-SEM modeling process, the following steps were carried out: (1) identification of the three attitude components (affective, cognitive, and conative) based on the theoretical model; (2) specification of the relationships between latent variables and their measurement indicators (outer model); (3) definition of the regression paths between the latent constructs (inner model). This approach allows a deeper and more complex understanding of the relationships between the different attitude components and their influence on actual system use. The results of the PLS-SEM help to identify the key factors that can enhance the efficiency and acceptance of DRS.

The validation of the outer model was performed using standard reliability and validity criteria. Internal consistency was confirmed as Cronbach's alpha, composite reliability (rhoC), and rhoA - all exceeded the recommended threshold of 0.70. Convergent validity was established since the Average Variance Extracted (AVE) for each construct was above the 0.50 cutoff (Hair Jr, 2020; Hair Jr et al., 2010, 2021). As shown in Table 3, all constructs demonstrated high reliability and stable internal consistency.

In the Fornell–Larcker test (Fornell and Larcker, 1981), the square root of the AVE for each construct exceeded its correlations with all other constructs, confirming adequate discriminant validity (Table 4). The Heterotrait–Monotrait Ratio of Correlations (HTMT) values were also below the recommended threshold of 0.90 in all cases (Henseler et al., 2015). In addition, 95 % bias-corrected and accelerated (BCa) confidence intervals were computed using bootstrapping with 5000 subsamples; the upper bounds of the CIs remained below 1.00, further supporting discriminant validity.

The inner model was evaluated by examining the path coefficients (β-values) between the latent constructs and the explained variance (R^2) of the endogenous variables (Chin, 1998; Hair Jr et al., 2010). The R^2 values were as follows: Cognitive = 0.400, Conative = 0.638, and Use = 0.269, indicating moderate to substantial explanatory power. All path coefficients were statistically significant based on bootstrapping with 5000 samples. The model's predictive relevance was further confirmed by positive Stone–Geisser Q^2 values for all endogenous constructs, supporting the robustness of the results. These results confirm that the measurement model meets all standard reliability and validity requirements. The constructs demonstrate strong internal consistency and convergent validity, while discriminant validity is supported by both the Fornell–Larcker and HTMT criteria. Together, these indicators confirm that the latent variables are well-defined, distinct, and robust, providing a solid foundation for the interpretation of the structural relationships in the PLS-SEM model.

4. Results

4.1. Impact of demographic characteristics

First, to determine which specific groups differed significantly, Tukey's HSD post-hoc tests were conducted following the ANOVA (Table 5). No statistically significant differences in REpont system usage frequency were observed for gender, age, income level, or living with a child under the age of six. For education, the difference between secondary school and primary school respondents was statistically significant (+0.178, $p < 0.05$), indicating higher usage among those with secondary education. University graduates did not differ significantly from primary school respondents (+0.028, $p > 0.05$), but they reported significantly lower usage than those with secondary education (–0.150, $p < 0.01$). For settlement type, no significant difference was observed between rural and urban residents (+0.036, $p > 0.05$). However, capital city residents reported significantly lower usage than both rural (–0.163, $p < 0.05$) and urban (–0.199, $p < 0.01$) residents.

To further explore how demographic characteristics interact in shaping REpont system usage patterns, a k-means cluster analysis was conducted. While ANOVA tests examine each variable independently, cluster analysis identifies groups of respondents who share similar demographic profiles across multiple variables simultaneously. This approach helps reveal compound effects that may not be visible when considering variables in isolation (Everitt et al., 2011). The primary segmentation used settlement type and education level, the two variables showing statistically significant differences in usage frequency in the ANOVA (Table 6). This choice ensured that the clustering focused on the most relevant demographic dimensions. ANOVA on the cluster means for usage revealed statistically significant differences ($p < 0.05$) and three clusters were clearly distinguishable. Cluster 1 consisted primarily of rural residents with secondary education. Cluster 2 included urban/capital residents with university degrees. Cluster 3 was dominated by urban residents with secondary education.

As a robustness check, a second k-means clustering was conducted using age, income, and education level. Although age and income were not individually significant in the earlier ANOVA, their combination with education level produced distinct usage patterns. Three clusters emerged: Cluster 1 with young, low-income, secondary-educated individuals; Cluster 2 with young–middle-aged, medium–high income, university-educated individuals, and Cluster 3 with middle-aged–older, low–medium income, mixed education. In this model, Cluster 2 again

Table 3
Reliability and convergent validity of constructs.

Construct	Cronbach's Alpha	rhoC	AVE	rhoA
Affective	0.892	0.894	0.740	0.905
Cognitive	0.919	0.919	0.694	0.921
Conative	0.790	0.793	0.501	0.826

Note: Discriminant validity was assessed using two complementary approaches: the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio of Correlations (HTMT) (Fornell and Larcker, 1981; Henseler et al., 2015).

Table 4
Summary of discriminant validity.

Construct Pair	Fornell–Larcker Criterion	HTMT Ratio < 0.90	HTMT CI Upper Bound < 1.00
Affective → Cognitive	0.860 > 0.577	0.631	0.640
Cognitive → Conative	0.833 > 0.696	0.799	0.806
Cognitive → Use	0.833 > 0.473	0.493	0.501
Conative → Use	0.708 > 0.446	0.478	0.487

Note: Fornell–Larcker criterion – the square root of AVE must be greater than the inter-construct correlations. HTMT ratio – values should be below 0.90 (or 0.85 for stricter assessments). HTMT confidence interval – the upper bound of the 95 % CI should be below 1.00.

Table 5
Significant and non-significant demographic group differences in the frequency of REpont system use according to ANOVA results.

Variable	Category	Deviation from mean
Significant demographic group differences		
Education	Primary school	−0.108
	Secondary school	+0.070
	University	−0.080
Region	Southern Great Plain	+0.050
	Southern Transdanubia	+0.026
	Northern Great Plain	+0.369
	Northern Hungary	−0.127
	Central Transdanubia	+0.130
	Central Hungary	−0.065
	Western Transdanubia	+0.059
Settlement	Rural	+0.002
	Urban	+0.038
	Capital	−0.162
Gender	Female	+0.015
	Male	−0.037
Age	18–29	+0.016
	30–39	−0.059
	40–59	+0.010
	60+	−0.008
Income	Low	+0.017
	Medium	+0.020
	High	−0.112
Children	No	−0.004
	Yes	+0.011

Note: Positive values indicate above-average use, negative values indicate below-average use. Deviations are calculated relative to the overall sample mean (3.231).

Table 6
Cluster profiles, REpont usage means, and significant differences.

Segmentation type	Cluster	Variables	Profile description	N	Mean usage	Significant difference ($p < 0.05$)
Primary segmentation (Settlement + Education)	1	Settlement: 1.00 (rural), Education: 2.18 (secondary)	Rural, secondary education	794	3.23	no significant difference
	2	Settlement: 2.23 (urban–capital), Education: 3.00 (university)	Urban/capital, university degree	772	3.16	lower than 3
	3	Settlement: 2.16 (urban), Education: 1.92 (secondary)	Urban, secondary education	1100	3.28	higher than 2
Robustness check (Age + Income + Education)	1	Age: 1.13 (18–29), Income: 1.25 (low), Education: 1.95 (secondary)	Young, low-income, secondary education	754	3.28	higher than 2
	2	Age: 1.68 (18–39), Income: 2.19 (medium–high), Education: 2.77 (university)	Young–middle-aged, high-income, university degree	365	3.10	lower than 1 and 3
	3	Age: 3.26 (40–59), Income: 1.71 (low–medium), Education: 2.37 (secondary–university)	Middle-aged–older, medium-income, mixed education	1547	3.24	higher than 2

showed the lowest usage levels, significantly below Clusters 1 and 3, confirming the pattern observed in the primary segmentation: higher education, especially when paired with certain socioeconomic profiles, is linked to reduced engagement with the REpont system. These descriptive patterns highlight the heterogeneity of consumer groups and provide context for the subsequent structural model analysis presented in Section 4.2 and 4.3.

4.2. Results of the structural model

The structural model (see above in Fig. 1) was evaluated to statistically test the hypothesized relationships between the three attitude components and their influence on the actual frequency of REpont system use. All analyses were performed on post-stratification weighted data, adjusted for gender, age, education level, and region to match the population distribution reported by the Hungarian Central Statistical Office (2024). The assessment followed established PLS-SEM procedures (Hair Jr et al., 2021), and was based on the analysis of path coefficients, explained variance (R^2), and bias-corrected confidence intervals obtained through nonparametric bootstrapping with 5000 resamples.

The results indicated that Affective had a strong and statistically significant positive effect on Cognitive ($\beta = 0.633$, 95 % CI [0.624, 0.641]), supporting the theoretical assumption that Affective attitudes promote the development of knowledge and beliefs about the system (Fig. 2). This finding implies that users' emotional attachment (e.g., satisfaction when using the system) plays an important role in shaping how they understand and evaluate its benefits. The strong affective–cognitive link highlights that positive feelings can serve as a foundation for informed engagement with the DRS. Cognitive had a strong and significant positive effect on Conative ($\beta = 0.799$, CI [0.792, 0.805]) and a moderate but significant direct effect on Actual Use ($\beta = 0.279$, CI [0.262, 0.296]). These results indicate that rational evaluations and perceived usefulness translate into behavioral intentions and, to a lesser extent, direct participation. In other words, when consumers perceive

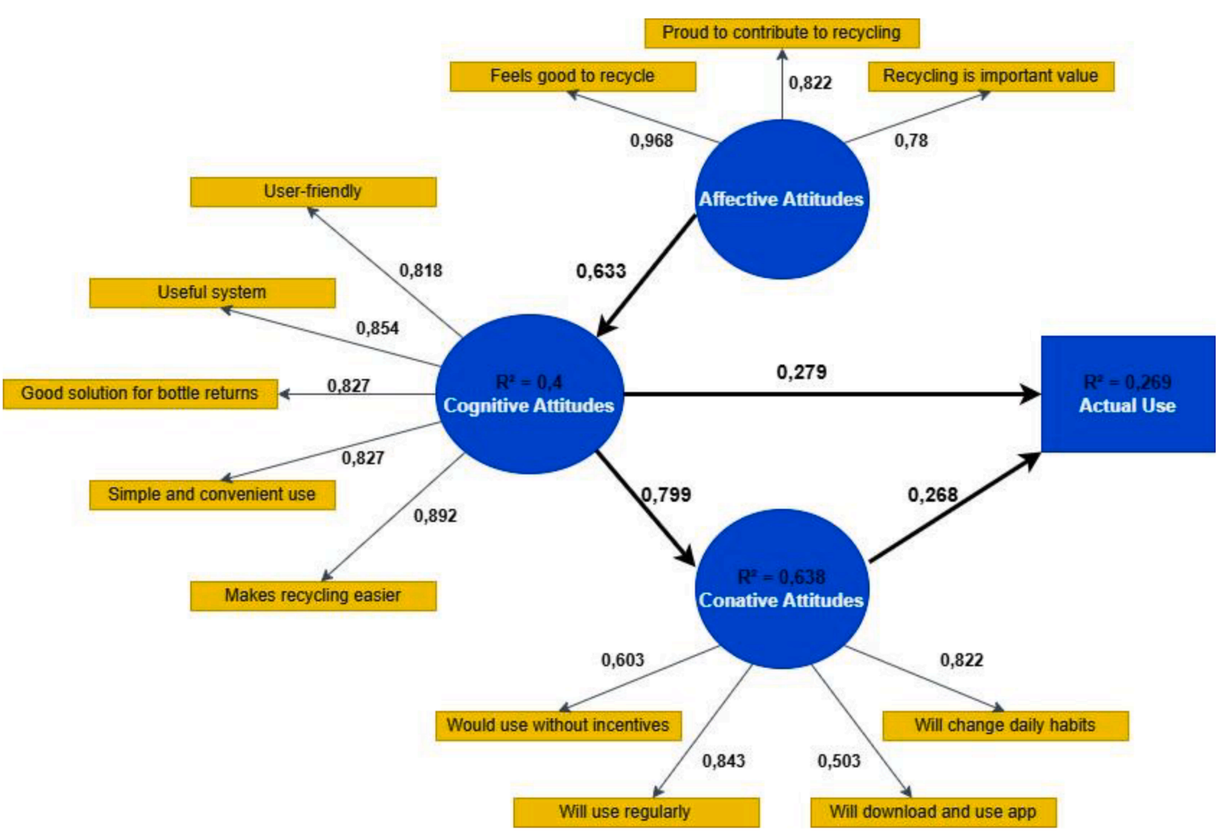

Fig. 2. PLS-SEM model of consumer attitudes toward REpont system use.

the system as efficient and valuable, they are more likely to form habits and engage repeatedly.

Conative also exerted a significant positive effect on Actual Use (β = 0.268, CI [0.250, 0.286]). Thus, it demonstrates that behavioral intentions are strong predictors of actual engagement. The comparable magnitudes of the conative-to-use and cognitive-to-use paths suggest that both habitual intention and cognitive evaluation have a great influence on real-world usage. The similar magnitude of the two direct effects on use suggests that both cognitive evaluations and conative intentions play comparable roles in determining actual system usage frequency, while the relatively lower R^2 for use indicates that additional, unmodeled behavioral determinants are likely influencing usage in real-world contexts. Beyond statistical significance, these results show substantive behavioral meaning. Emotional, cognitive, and conative components together explain a large portion of user motivation. This supports the theoretical assumption that sustained engagement with DRS depends not only on knowledge but also on affective and habitual commitment. All hypothesized structural paths were statistically supported at the 5 % level, as the 95 % confidence intervals did not include zero.

An examination of total effects revealed several important indirect relationships (Table 7). Affective exerted a significant indirect effect on Conative via Cognitive (β = 0.506) and on Actual Use through the sequential mediation of Cognitive and Conative (β = 0.224). Similarly, Cognitive influenced Actual Use indirectly through Conative (β = 0.214). These findings highlight the sequential structure of attitudinal processes, in which affective responses shape cognitive evaluations, which in turn drive behavioral intentions and actual usage. Moreover, these results confirm that the three attitudinal components operate in a causal sequence rather than as parallel predictors. The relatively high indirect effect from affective to use suggests that emotional engagement exerts a long-range influence on real behavior, mediated through users' knowledge and intentions. This emphasizes the practical importance of fostering positive emotional experiences to strengthen sustained participation in the DRS. Beyond statistical confirmation, the magnitudes of these indirect paths indicate important behavioral relevance: emotional and cognitive drivers jointly activate habitual intentions, thereby promoting consistent and repeated system use.

Table 7
Indirect effects among latent constructs.

Path	Indirect Effect (β)	95 % CI	Interpretation
Affective → Conative (via Cognitive)	0.506	[0.499, 0.513]	Strong and significant indirect effect. Affective attitudes increase cognitive evaluations, which in turn strengthen behavioral intentions.
Affective → Use (via Cognitive)	0.177	[0.164, 0.189]	Moderate indirect effect through cognitive only. Emotional engagement increases understanding and perceived usefulness, which directly promotes use.
Affective → Use (via Cognitive → Conative)	0.135	[0.126, 0.144]	Significant sequential mediation effect: emotions → cognition → intention → use.
Affective → Use (total indirect effect)	0.224	[0.210, 0.239]	Combined indirect effect through both cognitive and conative paths, confirming that affective influence on behavior operates entirely through mediated routes.
Cognitive → Use (via Conative)	0.214	[0.203, 0.226]	Strong and significant indirect effect. Cognitive evaluations indirectly promote usage through intentions and habitual engagement.

Note: All indirect effects are significant at $p < 0.05$.

4.3. Interpretation of the structural results

The results of the PLS-SEM confirmed that the conative attitude component plays a central role in explaining actual participation in the REpont system (Table 8). Behavioral intentions and habitual patterns captured by the conative dimension showed a direct and significant positive relationship with usage frequency, indicating that intention-focused interventions are particularly effective in promoting repeated engagement. With respect to H1, the results supported the assumption that more positive attitudes toward the REpont system are associated with greater behavioral integration, reflected in regular and consistent system use. Both affective and conative attitudes showed significant positive associations with usage, where the conative component exerted a direct influence on behavior, and the affective component influenced it indirectly through cognitive and conative pathways. This pattern suggests that positive attitudes are translated into behavioral consistency through emotional and habitual reinforcement. H2 was not supported, as cognitive attitudes proved to be stronger predictors of behavioral intentions than affective attitudes. Emotional responses such as satisfaction, pride, or enjoyment significantly enhanced cognitive evaluations and perceived usefulness, which strengthened behavioral intentions. Although affective attitudes were not modeled to have a direct path to actual usage, their indirect influence through cognitive and conative components was significant, demonstrating that emotional motivation acts as a catalyst for both rational appraisal and habitual engagement.

Regarding H3, the results partially supported the initial expectation. Cognitive evaluations exhibited a moderate yet statistically significant effect on system use (β = 0.279, $p < 0.05$), suggesting that knowledge and perceived system effectiveness positively contribute to engagement. However, segmentation analyses revealed that in certain demographic clusters, particularly among highly educated urban residents, higher awareness did not necessarily correspond to higher usage. This finding indicates that the influence of cognitive attitudes is context-dependent, potentially constrained by unfavorable operational conditions and user experience. Finally, H4 was strongly supported by the data. Cognitive attitudes mediated the relationship between affective attitudes and consumers' conative responses (intentions and actual use). Affective attitudes significantly promoted cognitive evaluations, which in turn reinforced behavioral intentions and usage frequency. This sequential mediation confirmed the theoretical assumption of the three-component model, illustrating a clear affective → cognitive → conative → use pathway in the case of the REpont system.

4. Discussion and implications

4.1. Interpretation of the findings

The results of this study highlight the complex and multidimensional nature of consumer engagement in the Hungarian REpont DRS. The adoption of the three-component (multidimensional) attitude model was driven by empirical evidence rather than theoretical preference. Factor analysis revealed a latent structure consistent with cognitive, affective, and conative dimensions, strengthening the idea that attitudinal architecture underlying circular behavior can be discovered inductively from data rather than imposed a priori.

The findings related to the first hypothesis demonstrate that more positive attitudes toward the REpont system are associated with greater behavioral integration. It means that users who evaluate the system favorably are more likely to use it regularly and consistently. This result aligns with the TPB, which identifies intention as the key determinant of behavior (Ajzen, 1991, 2020), and extends it by showing that in circular contexts, repeated DRS participation represents a form of behavioral routinization rather than a one-time act. In this sense, attitudes toward the REpont system appear to reflect both rational and habitual components of pro-environmental behavior.

Table 8
Summary of the results of the hypothesis.

Hypothesis	Statement	Result	Explanation
H1	More positive attitudes toward the REpont system are associated with greater behavioral integration, reflected in the regular and consistent use of the system.	Supported	Affective and conative attitudes both positively influence system use. The conative component exerts a direct significant effect ($\beta = 0.268$, $p < 0.05$), while affective attitudes influence use indirectly through cognitive and conative pathways (total indirect $\beta = 0.224$, $p < 0.05$). This confirms that positive attitudes toward the REpont system foster regular and consistent usage through both emotional engagement and behavioral intention.
H2	Affective attitudes have a stronger positive effect on consumers' intentions to participate in the REpont system than cognitive attitudes.	Not supported	Affective attitudes significantly influence behavioral intentions indirectly through cognitive evaluations, but the direct cognitive effect on intentions ($\beta = 0.799$) is stronger than the indirect affective influence ($\beta = 0.506$). Thus, emotional engagement plays a substantial yet secondary role in shaping behavioral intentions, operating primarily through cognitive appraisal.
H3	Cognitive attitudes have a weak positive effect on REpont system use, due to the system's initial operational challenges and limited user experience.	Partially supported	Cognitive → Use ($\beta = 0.279$, $p < 0.05$) showed a moderate positive effect overall. However, demographic and cluster analyses revealed subgroups (urban, highly educated) with reduced usage despite higher awareness. Thus, the cognitive effect exists but is context-dependent.
H4	Cognitive attitudes mediate the influence of affective attitudes on consumers' conative responses (intentions and actual use) of the REpont System.	Supported	The results confirmed a sequential mediation pathway in which cognitive attitudes mediate the influence of affective attitudes on both behavioral intentions and actual system use. Affective attitudes strongly enhanced cognitive evaluations ($\beta = 0.633$, $p < 0.05$), which in turn reinforced behavioral intentions (Cognitive → Conative, $\beta = 0.799$, $p < 0.05$) and usage frequency (Conative → Use, $\beta = 0.268$, $p < 0.05$). The indirect effects (Affective → Conative via Cognitive, $\beta = 0.506$; Affective → Use via Cognitive and Conative, $\beta = 0.224$; both $p < 0.05$) confirmed full mediation.

The second hypothesis tested the relative strength of affective and cognitive components, revealing that cognitive attitudes have a stronger and more direct impact on participation. This finding is in line with the theoretical expectation that rational evaluation and perceived usefulness are key drivers of engagement in pro-environmental systems. However, emotional responses such as pride, satisfaction, and enjoyment were found to play a supportive role by strengthening cognitive evaluations and reinforcing motivation. This interaction reflects the growing recognition in behavioral research that affective experiences indirectly sustain environmental actions through cognitive and conative pathways (Best and Mayerl, 2013; Han and Kim, 2010). This cognitive dominance confirms the rational-choice assumption of TPB but also highlights the growing importance of emotional and moral factors in shaping behavioral intentions (Ajzen, 2020; Klöckner, 2013). From this perspective, the Hungarian case illustrates that emotional commitment complements rather than replaces rational assessment. While cognitive understanding directly drives participation, emotional and habitual reinforcement maintain long-term engagement. These results are consistent with previous evidence that affective and conative factors jointly stabilize sustainable behavior (Best and Mayerl, 2013; Mosler et al., 2008). Moreover, Escario et al. (2020) emphasized that perceived system effectiveness mediates the relationship between attitudes and waste-reduction behaviors, implying that negative user experiences can weaken the cognitive pathway. Thus, although cognitive attitudes represent the strongest predictor of participation in the REpont system, emotional engagement remains essential for sustaining consistent recycling behavior over time.

Contrary to the third hypothesis, the cognitive component was not negligible but exhibited a moderate and statistically significant influence on system use. This suggests that knowledge and perceived usefulness still matter, even when the system operates under imperfect conditions. However, this cognitive influence was uneven across demographic clusters: urban and highly educated respondents reported lower participation despite higher awareness levels. This paradox is consistent with previous studies showing that cognitive evaluations can fail to translate into action when contextual or infrastructural barriers weaken trust and convenience (Knickmeyer, 2020; Roca et al., 2022). In the REpont case, operational barriers (e.g., crowded return points, long waiting times, or the stigmatization of redemption areas) may have weakened the positive effects of knowledge, confirming that environmental cognition alone cannot ensure behavioral consistency. These findings resonate with the "value–action gap" identified by Kollmuss and Agyeman (2002), emphasizing that structural and emotional factors mediate the pathway from belief to behavior.

The fourth hypothesis explored the relationship among cognitive, affective, and conative dimensions, revealing that cognitive attitudes mediate the influence of affective attitudes on conative responses. This result aligns with the theoretical view that emotional experiences can indirectly encourage behavioral engagement through their positive influence on cognitive evaluations (Best and Mayerl, 2013; Tang et al., 2022). In the context of a newly implemented DRS, emotional engagement appears to improve the translation of cognitive understanding into behavioral intention and habitual use. This pattern reflects a broader shift in sustainability research toward integrated models that combine attitudinal, emotional, and contextual factors (Han, 2020; Wiśniewska et al., 2025).

The results indicate that while rational evaluations contribute to engagement, it is the emotional and habitual reinforcement that ensures long-term participation in circular systems. From a theoretical standpoint, these findings extend the application of the three-component attitude model to the domain of DRS. Whereas most of the prior studies have focused primarily on external incentives and system convenience (Oke et al., 2020; Roca et al., 2022), this research demonstrates that internalized affective and conative drivers are equally, if not more, influential in maintaining participation. By empirically validating the mediating role of emotions, the study also contributes to bridging behavioral theories (e.g., TPB and VBN), illustrating that moral and affective commitment can activate behavior even in the absence of strong perceived control. The proposed cognitive–affective–conative sequence thus provides a theoretically grounded mechanism through which attitudes evolve into sustainable habits in circular contexts.

4.2. Managerial and policy implications

The managerial and policy implications of these findings are outlined below. For operators and retailers, it is not sufficient to emphasize the technical or economic aspects of the system; emotional and experiential dimensions must also be addressed. Communication strategies should focus on strengthening positive emotions associated with participation, such as pride and contribution to environmental protection, while reducing sources of frustration related to waiting times or machine availability. Ensuring smooth operation and user-friendly interfaces can strengthen perceived system effectiveness, which mediates the relationship between attitudes and behavior (Escario et al., 2020). Simple interventions, such as instant feedback messages on screens or mobile applications showing collective environmental impact, can transform recycling from a routine obligation into a rewarding experience.

At the policy level, the Hungarian case underlines the importance of context-sensitive design. Overcrowded or stigmatized return points may discourage even environmentally conscious users, highlighting the need for more decentralized and socially inclusive implementation. Policymakers should consider expanding the density of return locations, improving maintenance schedules, and securing that redemption areas remain clean and accessible. Moreover, awareness campaigns should not only inform but also inspire, combining factual messages with emotional narratives that emphasize community and shared responsibility. This approach aligns with the understanding that the effectiveness of monetary incentives depends on the perceived fairness and social acceptance of the system (Guagnano et al., 1995; Steg and Vlek, 2009).

Finally, the results have educational implications. Environmental education and sustainability communication programs should not rely solely on cognitive instruction but should also incorporate emotional and experiential learning. Encouraging students and citizens to reflect on the personal satisfaction and collective benefits of recycling can strengthen emotional attachment to sustainable routines. Providing feedback on local return rates, waste reductions, or CO_2 savings may further bridge the gap between knowledge and action.

4.3. Limitations and future research

This paper extends the understanding of pro-environmental behavior in an emerging circular system by empirically demonstrating that attitudes are multidimensional, emotionally grounded, and shaped by contextual realities. The first limitation of this study lies in the potential impact of voluntary response bias inherent in online surveys. While demographic weighting was applied to approximate the population structure and improve representativeness, such adjustments cannot fully account for attitudinal or motivational differences that may influence participation. Consequently, the data may slightly overrepresent individuals who are more environmentally conscious or more familiar with recycling systems. Moreover, online recruitment may have excluded segments of the population with limited internet access or lower digital literacy. Together, these factors could affect the strength or direction of certain relationships observed in the analysis. Furthermore, the cross-sectional nature of the data restricts causal inference, as the observed relationships between cognitive, affective, and conative components reflect associations rather than temporal effects. Together, these factors suggest that the findings should be interpreted with appropriate caution, acknowledging that the sample achieves demographic representativeness but may not entirely capture the full behavioral diversity of the target population.

Future research could address these limitations by employing longitudinal data or behavioral tracking of actual system use to capture temporal dynamics. Experimental approaches could also test the causal effects of targeted interventions on different attitudinal components. Moreover, qualitative approaches may provide deeper understanding of contextual factors, such as urban challenges (e.g., the disruptive presence of marginalized groups at redemption points) or the stigmatization of collection sites, influence consumer engagement and trust. It should also be noted that the Hungarian DRS operates in an early-stage, concession-based framework that differs structurally from the long-established, industry-led systems in Northern Europe. Thus, the generalizability of findings to other national contexts may be limited. Future cross-country comparisons could clarify whether the attitudinal mechanisms observed here are context-specific or represent broader behavioral patterns of circular participation.

5. Conclusion

This study examined consumer participation in the newly introduced Hungarian REpont DRS through the three-component attitude model. The results demonstrate that emotional commitment raises favorable cognitive assessments, which in turn drive intentions and habitual use patterns. This sequential process highlights that pro-environmental behavior is not only driven by rational evaluations but is deeply embedded in emotional responses and routines. The study's novelty lies in applying the three-component attitude model to a real-world circular economy intervention at the national level, providing one of the first empirical validations of this theoretical framework in the context of DRS. Methodologically, the research extends the literature by combining PLS-SEM with a large, demographically weighted sample, enabling robust assessment of both direct and indirect attitudinal pathways. Theoretically, it refines our understanding of how affective, cognitive, and conative components interact in shaping sustained pro-environmental behavior, offering a structured model for analyzing consumer engagement across similar policy tools.

The findings offer practical recommendations for managers and policymakers by emphasizing that system effectiveness depends not only on technical design and financial incentives but also on addressing social and infrastructural challenges (e.g., overcrowded machines and the presence of marginalized individuals at redemption points). This research contributes to connecting the gap between behavioral theory and environmental policy design. It highlights that long-term success of DRS depends on emotional and habitual engagement as much as on technological or economic efficiency, emphasizing a human-centered approach to circular participation. In a broader sense, the findings offer implications for circular economy strategies. Promoting sustainable consumption and waste-return behavior requires not only financial or infrastructural incentives, but also emotional engagement and the normalization of pro-environmental routines. Encouraging positive affect and habitual participation can strengthen citizens' psychological commitment to circular practices, making behavioral change more resilient and self-sustaining over time. Based on the above, decision-makers can design interventions that encourage durable, socially inclusive, and value-driven sustainability transitions.

Future research should build on these findings and the above-mentioned limitations by employing longitudinal or experimental designs to capture causal dynamics among the attitudinal dimensions. Behavioral tracking methods could complement survey data to better reflect actual participation in the REpont system. Qualitative approaches are also recommended to explore how contextual and social factors (e.g., local infrastructure, public trust, or perceived stigma at redemption points) that influence or shape user engagement. Cross-country comparative studies could further test whether the attitudinal mechanisms identified here are context-specific or represent broader patterns within circular economy participation. Together, these directions can support the development of more behaviorally grounded and socially inclusive DRS policies.

CRediT authorship contribution statement

József Ráti: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zalán Márk Maró:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A3

Table A1
Results of the factor analysis.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	13.62079	10.80011	0.6853	0.6853
Factor2	2.82068	0.87266	0.1419	0.8272
Factor3	1.94801	1.23087	0.0980	0.9252
Factor4	0.71715	0.12729	0.0361	0.9613
Factor5	0.58985	0.06862	0.0297	0.9910
Factor6	0.52123	0.12010	0.0262	1.0172
Factor7	0.40113	0.06103	0.0202	1.0374
Factor8	0.34011	0.06419	0.0171	1.0545
Factor9	0.27592	0.05849	0.0139	1.0683
Factor10	0.21743	0.06928	0.0109	1.0793
Factor11	0.14815	0.03276	0.0075	1.0867
Factor12	0.11539	0.06305	0.0058	1.0925
Factor13	0.05233	0.02876	0.0026	1.0952
Factor14	0.02357	0.01150	0.0012	1.0964
Factor15	0.01207	0.01959	0.0006	1.0970
Factor16	−0.00752	0.00993	−0.0004	1.0966
Factor17	−0.01745	0.00451	−0.0009	1.0957
Factor18	−0.02197	0.01047	−0.0011	1.0946
Factor19	−0.03244	0.01582	−0.0016	1.0930
Factor20	−0.04826	0.01012	−0.0024	1.0906
Factor21	−0.05838	0.00886	−0.0029	1.0876
Factor22	−0.06724	0.00915	−0.0034	1.0842
Factor23	−0.07639	0.00238	−0.0038	1.0804
Factor24	−0.07877	0.01108	−0.0040	1.0764
Factor25	−0.08985	0.00165	−0.0045	1.0719
Factor26	−0.09150	0.00969	−0.0046	1.0673
Factor27	−0.10119	0.00212	−0.0051	1.0622
Factor28	−0.10331	0.02500	−0.0052	1.0570
Factor29	−0.12831	0.00712	−0.0065	1.0506
Factor30	−0.13542	0.01153	−0.0068	1.0437
Factor31	−0.14695	0.01069	−0.0074	1.0363
Factor32	−0.15764	0.00180	−0.0079	1.0284
Factor33	−0.15943	0.03836	−0.0080	1.0204
Factor34	−0.19780	0.00983	−0.0100	1.0104
Factor35	−0.20763	.	−0.0104	1.0000

Table A2
Items excluded from the final models.

Question	Potential Construct
Recycling significantly reduces the amount of waste sent to landfills.	Environmental knowledge
Recycling contributes to the fight against climate change.	Environmental knowledge
Recycling is essential for a sustainable lifestyle.	Environmental knowledge
I believe that using the REpont system is beneficial for the environment.	Perceived usefulness
I enjoy using the REpont system.	Affective attitude
I will recommend the REpont system to others.	Behavioral intention
Using the REpont system helps me manage plastic and glass waste more efficiently.	Perceived usefulness
Using the REpont system contributes to making me more environmentally conscious.	Perceived usefulness
The REpont system is easy to learn to use.	Perceived ease of use
I support the REpont system because I think it is an effective solution to waste problems.	Normative belief
I consider participation in selective waste collection important for environmental protection.	Normative belief
The 50 forint refund motivates me to use the REpont system.	Financial incentive

(*continued on next page*)

Table A2 (*continued*)

Question	Potential Construct
I am satisfied with the REpont system.	User satisfaction
The REpont system provides financial benefits for me.	Perceived financial benefit
How important do you consider recycling?	Environmental value
I find selective waste collection difficult.	Perceived difficulty
I do not have enough information about recycling.	Perceived knowledge
There are no adequate opportunities for recycling near me.	Perceived behavioral control
I feel that recycling is not effective enough.	Perceived effectiveness
I do not have enough time for selective waste collection.	Perceived barrier
I do not have enough space at home to collect waste selectively.	Perceived barrier
Information about the REpont system is easily accessible.	Perceived knowledge
How often do you plan to use the REpont system in the future?	Behavioral intention
I will recommend the REpont system to others.	Behavioral intention

Table A3
Other survey questions.

Question	Category
What is your age?	Demographic
What is your gender?	Demographic
What is your highest level of education?	Demographic
What is your monthly income (compared to the Hungarian national net average of 414,000 HUF)?	Demographic
What is your postal code of residence?	Demographic
How many people live in your household, including yourself?	Demographic
How often do you collect waste selectively?	Behavioral
Is there a child under 18 years old living in your household?	Dummy
Have you heard about the REpont system?	Dummy
Have you been informed that bottles must be returned uncompressed and with an undamaged barcode?	Dummy
Have you been adequately informed about how to use the REpont system?	Dummy
Type of residence (Rural / Urban / Capital)	Contextual
How far (in kilometers) is the nearest REpont machine from your home?	Contextual
How long does it usually take (in minutes) to reach the nearest REpont machine?	Contextual
How much time (in minutes) does it usually take to use the REpont machine?	Contextual
Do you plan to use the REpont system in the future?	Behavioral intention
Which option do you choose most often? (Store voucher / Cash / Bank transfer refund)	Behavioral preference

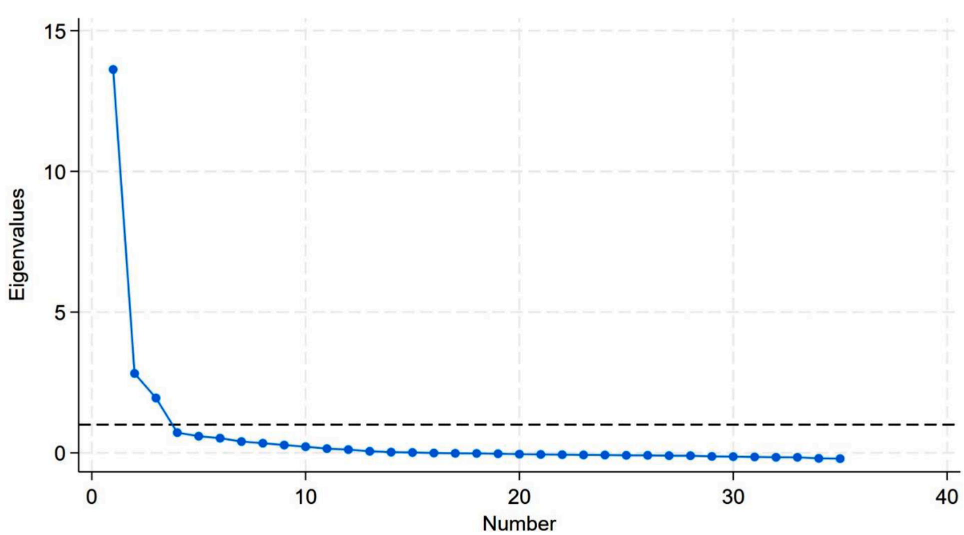

Fig. A1. Cattell's scree plot.

Data availability

Data will be made available on request.

References

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Ajzen, I., 2020. The theory of planned behavior: frequently asked questions. Hum. Behav. Emerg. Technol. 2 (4), 314–324. https://doi.org/10.1002/hbe2.195.

Ajzen, I., Fishbein, M., 2000. Attitudes and the attitude-behavior relation: reasoned and automatic processes. Eur. Rev. Soc. Psychol. 11 (1), 1–33. https://doi.org/10.1080/14792779943000116.

Al Mamun, A., Hayat, N., Masud, M.M., Makhbul, Z.K.M., Jannat, T., Salleh, M.F.M., 2022. Modelling the significance of value-belief-norm theory in predicting solid waste management intention and behavior [Original Research]. Front. Environ. Sci. 10, 2022. https://doi.org/10.3389/fenvs.2022.906002. *Volume*.

Al Mamun, A., Ma, Y., Nurul Hassan Reza, M., Ahmad, J., Wan Mohd Hirwani Wan, H., Lili, Z., 2024. Predicting attitude and intention to reduce food waste using the environmental values-beliefs-norms model and the theory of planned behavior. Food Qual. Prefer. 120, 105247. https://doi.org/10.1016/j.foodqual.2024.105247.
AlSaleh, D., Thakur, R., 2019. Impact of cognition, affect, and social factors on technology adoption. Int. J. Technol. Market. 13 (2), 178–200. https://doi.org/10.1504/ijtmkt.2019.102266.
Ari, E., Yilmaz, V., 2023. Investigation of attitudes and behaviors towards recycling with theory planned behavior. J. Econ. Culture Soc. (66), 145–161. https://doi.org/10.26650/JECS2021-1042348.
Barr, S., 2007. Factors influencing environmental attitudes and behaviors:a U.K. Case study of household waste management. Environ. Behav. 39 (4), 435–473. https://doi.org/10.1177/0013916505283421.
Bartlett, M.S., 1954. A note on the multiplying factors for various ?^{2}Approximations. J. Royal Statist. Soc. Series B (Methodological) 16 (2), 296–298. http://www.jstor.org/stable/2984057.
Best, H., Mayerl, J., 2013. Values, beliefs, attitudes: an empirical study on the structure of environmental concern and recycling participation. Soc. Sci. Q. 94 (3), 691–714. https://doi.org/10.1111/ssqu.12010.
Biswas, A., Licata, J.W., McKee, D., Pullig, C., Daughtridge, C., 2000. The recycling cycle: an empirical examination of consumer waste recycling and recycling shopping behaviors. J. Public Policy Market. 19 (1), 93–105. https://doi.org/10.1509/jppm.19.1.93.16950.
Borucka, A., Grzelak, M., 2025. Deposit–Refund system as a strategy to drive sustainable energy transition on the example of Poland. Sustainability. 17 (3), 1030. https://www.mdpi.com/2071-1050/17/3/1030.
Breckler, S.J., 1984. Empirical validation of affect, behavior, and cognition as distinct components of attitude. J. Pers. Soc. Psychol. 47 (6), 1191–1205. https://doi.org/10.1037/0022-3514.47.6.1191.
Chang, I.-H., Hsiao, Y.-C., 2025. How does environmental cognition promote low-carbon travel intentions? The mediating role of green perceived value and the moderating role of electronic word-of-mouth. Sustainability. 17 (4), 1383. https://www.mdpi.com/2071-1050/17/4/1383.
Chin, W., Cheah, J.-H., Liu, Y., Ting, H., Lim, X.-J., Cham, T.H., 2020. Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research. Industr. Manag. Data Syst. 120 (12), 2161–2209. https://doi.org/10.1108/imds-10-2019-0529.
Chin, W.W., 1998. The partial least squares approach to structural equation modeling. Modern Methods For Business Research. Psychology Press, pp. 295–336.
DeBell, M., Krosnick, J.A., 2009. ANES Technical Report Series.
Diamantopoulos, A., Schlegelmilch, B.B., Sinkovics, R.R., Bohlen, G.M., 2003. Can socio-demographics still play a role in profiling green consumers? A review of the evidence and an empirical investigation. J. Bus. Res. 56 (6), 465–480. https://doi.org/10.1016/S0148-2963(01)00241-7.
Escario, J.-J., Rodriguez-Sanchez, C., Casaló, L.V., 2020. The influence of environmental attitudes and perceived effectiveness on recycling, reducing, and reusing packaging materials in Spain. Waste Manag. 113, 251–260. https://doi.org/10.1016/j.wasman.2020.05.043.
Everitt, B., Landau, S., Leese, M., & Stahl, D., 2011. Cluster analysis *Wiley Series in Probability and Statistics*. https://doi.org/10.1002/9780470977811.
Field, A., 2024. Discovering Statistics Using IBM SPSS Statistics. Sage publications limited.
Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Market. Res. 18 (1), 39–50. https://doi.org/10.1177/002224378101800104.
Fraj, E., Martinez, E., 2007. Ecological consumer behaviour: an empirical analysis. Int. J. Consum. Stud. 31 (1), 26–33. https://doi.org/10.1111/j.1470-6431.2006.00565.x.
Fricker, R.D., 2008. Sampling methods for web and e-mail surveys. The SAGE Handbook of Online Research Methods. SAGE Publications Ltd, London.
Geiger, S.M., Fischer, D., Schrader, U., 2018. Measuring what matters in sustainable consumption: an integrative framework for the selection of relevant behaviors. Sustain. Develop. 26 (1), 18–33. https://doi.org/10.1002/sd.1688.
Guagnano, G.A., Stern, P.C., Dietz, T., 1995. Influences on attitude-behavior relationships:a natural experiment with curbside recycling. Environ. Behav. 27 (5), 699–718. https://doi.org/10.1177/0013916595275005.
Gyrd-Jones, R.I., Kornum, N., 2013. Managing the co-created brand: value and cultural complementarity in online and offline multi-stakeholder ecosystems. J. Bus. Res. 66 (9), 1484–1493. https://doi.org/10.1016/j.jbusres.2012.02.045.
Haenlein, M., Kaplan, A.M., 2004. A beginner's guide to partial least squares analysis. Understand. Statist. 3 (4), 283–297. https://doi.org/10.1207/s15328031us0304_4.
Hair, J., Babin, B., Anderson, R., Black, W., 2019. Multivariate Data analysis. England Pearson Prentice. References-Scientif. Res. Publish.(Nd).
Hair, J.F., 2014. A Primer On Partial Least Squares Structural Equation Modeling (PLS-SEM). SAGE Publishing.
Hair Jr, J.F., 2020. Next-generation prediction metrics for composite-based PLS-SEM. Industr. Manag. Data Syst. 121 (1), 5–11. https://doi.org/10.1108/imds-08-2020-0505.
Hair Jr, J.F., Babin, B.J., Anderson, R.E., 2010. A Global P-Erspect-Ivie. Kennesaw State University, Kennesaw, pp. 2186–2212.
Hair Jr, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S., 2021. Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A workbook. Springer Nature. https://doi.org/10.1007/978-3-030-80519-7.
Han, H., 2020. Theory of green purchase behavior (TGPB): a new theory for sustainable consumption of green hotel and green restaurant products. Bus. Strategy. Environ. 29 (6), 2815–2828. https://doi.org/10.1002/bse.2545.
Han, H., Kim, Y., 2010. An investigation of green hotel customers' decision formation: developing an extended model of the theory of planned behavior. Int. J. Hosp. Manage 29 (4), 659–668. https://doi.org/10.1016/j.ijhm.2010.01.001.
Hansla, A., Gamble, A., Juliusson, A., Gärling, T., 2008. The relationships between awareness of consequences, environmental concern, and value orientations. J. Environ. Psychol. 28 (1), 1–9. https://doi.org/10.1016/j.jenvp.2007.08.004.
Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Market. Sci. 43 (1), 115–135. https://doi.org/10.1007/s11747-014-0403-8.
Ile, A.L., Caizer, A.D., Dragan, A., 2025. Challenges in transitioning to a circular economy: a spatial analysis of socioeconomic factors affecting the adoption of the deposit-return system. Environments. 12 (5), 142. https://www.mdpi.com/2076-3298/12/5/142.
Kaiser, H.F., 1974. An index of factorial simplicity. Psychometrika 39 (1), 31–36. https://doi.org/10.1007/BF02291575.
Klöckner, C.A., 2013. A comprehensive model of the psychology of environmental behaviour—A meta-analysis. Global Environ. Change 23 (5), 1028–1038. https://doi.org/10.1016/j.gloenvcha.2013.05.014.
Knickmeyer, D., 2020. Social factors influencing household waste separation: a literature review on good practices to improve the recycling performance of urban areas. J. Clean. Prod. 245, 118605. https://doi.org/10.1016/j.jclepro.2019.118605.
Kollmuss, A., Agyeman, J., 2002. Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior? Environ. Educ. Res. 8 (3), 239–260. https://doi.org/10.1080/13504620220145401.
Konstantoglou, A., Fotiadis, T., Folinas, D., Falaras, A., Rotsios, K., 2023. Accessing consumer perceptions of the effectiveness of the deposit refund system. Sustainability. 15 (12), 9429. https://www.mdpi.com/2071-1050/15/12/9429.
Kosinski, M., Matz, S.C., Gosling, S.D., Popov, V., Stillwell, D., 2015. Facebook as a research tool for the social sciences: opportunities, challenges, ethical considerations, and practical guidelines. Am. Psycholog. 70 (6), 543.
Kremel, A., 2024. Consumer behaviour in a circular system – How values promote and hinder the participation of young adults in the Swedish deposit-refund system for beverage packaging. Circ. Econ. Sustain. 4 (2), 1427–1446. https://doi.org/10.1007/s43615-023-00333-7.
Langenbach, B.P., Berger, S., Baumgartner, T., Knoch, D., 2020. Cognitive resources moderate the relationship between pro-environmental attitudes and green behavior. Environ. Behav. 52 (9), 979–995. https://doi.org/10.1177/0013916519843127.
Lee, J.-S., Hsu, L.-T., Han, H., Kim, Y., 2010. Understanding how consumers view green hotels: how a hotel's green image can influence behavioural intentions. J. Sustain. Tourism 18 (7), 901–914. https://doi.org/10.1080/09669581003777747.
Loosveldt, G., Sonck, N., 2008. An evaluation of the weighting procedures for an online access panel survey. Surv. Res. Methods 2 (2), 93–105. https://doi.org/10.18148/srm/2008.v2i2.82.
Lowry, P.B., Gaskin, J., 2014. Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: when to choose it and how to use it. IEEe Trans. Prof. Commun. 57 (2), 123–146. https://doi.org/10.1109/TPC.2014.2312452.
Martinho, G., Alves, A., Santos, P., Ramos, M., 2024. Social evaluation of a Deposit and Refund System pilot project for polyethylene terephthalate packaging. Environ. Chall. 15, 100894. https://doi.org/10.1016/j.envc.2024.100894.
McCarty, J.A., Shrum, L.J., 2001. The influence of individualism, collectivism, and locus of control on environmental beliefs and behavior. J. Public Policy Market. 20 (1), 93–104. https://doi.org/10.1509/jppm.20.1.93.17291.
Miafodzyeva, S., Brandt, N., 2013. Recycling behaviour among householders: synthesizing determinants via a meta-analysis. Waste BioMass Valorization. 4 (2), 221–235. https://doi.org/10.1007/s12649-012-9144-4.
Mosler, H.-J., Tamas, A., Tobias, R., Rodríguez, T.C., Miranda, O.G., 2008. Deriving interventions on the basis of factors influencing behavioral intentions for waste recycling, composting, and reuse in Cuba. Environ. Behav. 40 (4), 522–544. https://doi.org/10.1177/0013916507300114.
Nameghi, E.N., Shadi, M., 2013. Affective and cognitive: consumers attitude toward practicing green (reducing, recycling & reusing). Int. J. Market. Stud. 5 (1), 157. https://doi.org/10.5539/ijms.v5n1p157.
Numata, D., 2016. Policy mix in deposit-refund systems - from schemes in Finland and Norway. Waste Manag. 52, 1–2. https://doi.org/10.1016/j.wasman.2016.05.003.
Ogiemwonyi, O., 2024. Determinants of green behavior (Revisited): a comparative study. Resour. Conserv. Recycl. Adv. 22, 200214. https://doi.org/10.1016/j.rcradv.2024.200214.
Ogiemwonyi, O., 2025. A conceptual review of circular economy position from a marketing perspective. Innovat. Green Develop. 4 (4), 100258. https://doi.org/10.1016/j.igd.2025.100258.
Ogiemwonyi, O., Jan, M.T., 2023. The correlative influence of consumer ethical beliefs, environmental ethics, and moral obligation on green consumption behavior. Resour. Conserv. Recycl. Adv. 19, 200171. https://doi.org/10.1016/j.rcradv.2023.200171.
Oke, A., Osobajo, O., Obi, L., Omotayo, T., 2020. Rethinking and optimising post-consumer packaging waste: a sentiment analysis of consumers' perceptions towards the introduction of a deposit refund scheme in Scotland. Waste Manag. 118, 463–470. https://doi.org/10.1016/j.wasman.2020.09.008.
Onel, N., Mukherjee, A., 2015. Understanding environmentally sensitive consumer behaviour: an integrative research perspective. World J. Entrepren., Manag. Sustain. Develop. 11 (1), 2–16. https://doi.org/10.1108/wjemsd-07-2014-0021.
Park, J., Ha, S., 2014. Understanding consumer recycling behavior: combining the theory of planned behavior and the norm activation model. Fam. Consum. Sci. Res. J. 42 (3), 278–291. https://doi.org/10.1111/fcsr.12061.

Pereira, L.M., Sanchez Rodrigues, V., Freires, F.G.M., 2024. Use of partial least squares structural equation modeling (PLS-SEM) to improve plastic waste management. Appl. Sci. 14 (2), 628. https://www.mdpi.com/2076-3417/14/2/628.

Petter, S., Straub, D., Rai, A., 2007. Specifying formative constructs in information systems research. MIS Quart. 31 (4), 623–656. https://doi.org/10.2307/25148814.

Phipps, D.J., Brown, D.J., Hagger, M.S., Hamilton, K., 2024. Can the cans: determinants of container deposit behavior before and after introduction of a container refund scheme. Behav. Sci. 14 (2), 112. https://www.mdpi.com/2076-328X/14/2/112.

Picuno, C., Gerassimidou, S., You, W., Martin, O., Iacovidou, E., 2025. The potential of Deposit Refund Systems in closing the plastic beverage bottle loop: a review. Resour., Conserv. Recycl. 212, 107962. https://doi.org/10.1016/j.resconrec.2024.107962.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879. https://doi.org/10.1037/0021-9010.88.5.879.

Reshetnikova, I., Lieskovska, V., Polous, O., Murin, V., 2025. The importance of the deposit-return system of packaging in the circular economy system: slovak innovation experience for Ukraine. Market. Manag. Innovat. 16 (1), 1–14. https://doi.org/10.21272/mmi.2.025.1-01.

Roca, M., Ayuso, S., Bala, A., Colomé, R., Fullana-i-Palmer, P., 2022. Evaluating the implementation of a packaging deposit and Refund System in Catalonia. Two surveys on citizenship's expected behaviour. Sci. Total Environ. 806, 150640. https://doi.org/10.1016/j.scitotenv.2021.150640.

Roca, M., Ayuso, S., Bala, A., Fullana-i-Palmer, P., 2020. What factors determine attitudes towards the implementation of a packaging deposit and refund system? A qualitative study of the perception of Spanish consumers. J. Environ. Manage 270, 110891. https://doi.org/10.1016/j.jenvman.2020.110891.

Schultz, P.W., Oskamp, S., 1996. Effort as a moderator of the attitude-behavior relationship: general environmental concern and recycling. Soc. Psychol. Q. 59 (4), 375–383. https://doi.org/10.2307/2787078.

Sidique, S.F., Lupi, F., Joshi, S.V., 2010. The effects of behavior and attitudes on drop-off recycling activities. Resour., Conserv. Recycl. 54 (3), 163–170. https://doi.org/10.1016/j.resconrec.2009.07.012.

Simmering, M.J., Fuller, C.M., Richardson, H.A., Ocal, Y., Atinc, G.M., 2015. Marker variable choice, reporting, and interpretation in the detection of common method variance:a review and demonstration. Organ. Res. Methods 18 (3), 473–511. https://doi.org/10.1177/1094428114560023.

Steg, L., Vlek, C., 2009. Encouraging pro-environmental behaviour: an integrative review and research agenda. J. Environ. Psychol. 29 (3), 309–317. https://doi.org/10.1016/j.jenvp.2008.10.004.

Steinmetz, S., Tijdens, K., & de Pedraza, P., 2009. Comparing different weighting procedures for volunteer web surveys: lessons to be learned from German and Dutch WageIndicator data.

Stern, P.C., Dietz, T., Abel, T., Guagnano, G.A., Kalof, L., 1999. A value-belief-norm theory of support for social movements: the case of environmentalism. Human Ecol. Rev. 6 (2), 81–97.

Stoeva, K., Alriksson, S., 2017. Influence of recycling programmes on waste separation behaviour. Waste Manag. 68, 732–741. https://doi.org/10.1016/j.wasman.2017.06.005.

Tabachnick, B.G., Fidell, L.S., Ullman, J.B., 2007. Using Multivariate Statistics, 5. Volpearson Boston, MA.

Tang, H., Ma, Y., Ren, J., 2022. Influencing factors and mechanism of tourists' pro-environmental behavior–Empirical analysis of the CAC-MOA integration model. Front. Psychol. 13, 1060404. https://doi.org/10.3389/fpsyg.2022.1060404.

Valle, P.O.D., Rebelo, E., Reis, E., Menezes, J., 2005. Combining behavioral theories to predict recycling involvement. Environ. Behav. 37 (3), 364–396. https://doi.org/10.1177/0013916504272563.

van Birgelen, M., Semeijn, J., Keicher, M., 2009. Packaging and proenvironmental consumption behavior:investigating purchase and disposal decisions for beverages. Environ. Behav. 41 (1), 125–146. https://doi.org/10.1177/0013916507311140.

Vaske, J.J., Jacobs, M.H., Sijtsma, M.T.J., Beaman, J., 2011. Can weighting compensate for sampling issues in internet surveys? Human Dimens. Wildlife 16 (3), 200–215. https://doi.org/10.1080/10871209.2011.571230.

Vicente, P., Reis, E., 2008. Factors influencing households' participation in recycling. Waste Manag. Res. 26 (2), 140–146. https://doi.org/10.1177/0734242x07077371.

Widodo, A., Wahid, N.A., 2018. Indonesian consumers' Purchase behaviour of green innovative product. Int. J. Eng. Technol. 7 (4.38), 1296–1300. https://doi.org/10.14419/ijet.v7i4.38.27809.

Wiśniewska, A., Liczmańska-Kopcewicz, K., Żemigała, M., 2025. Cognitive and affective antecedents of consumer engagement in green innovation processes. Sustain. Futures 9, 100750. https://doi.org/10.1016/j.sftr.2025.100750.