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Extending the Technology Acceptance Model to a Circular Economy Context: A Study of Hungary's REpont Deposit-Refund System

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ABSTRACT

The aim of the study is to examine the public acceptance of the deposit-refund system (DRS), introduced in the European Union, through an extended version of the Technology Acceptance Model (TAM). The research supplemented the classic constructs of TAM (behavioral intension, perceived usefulness, and perceived ease of use) with environmental consciousness, social pressure, financial incentives, and informational factors. According to the results of structural equation modeling (SEM) conducted on a representative, national Hungarian sample with 1005 respondents, perceived usefulness is the strongest predictor of behavioral intention, while social norms and environmental concerns also have a positive effect. Financial incentives did not influence intention but directly increased actual use. One of the most interesting findings is the paradoxical effect of information: higher levels of self-reported information were associated with lower perceived usefulness, possibly due to cognitive dissonance or increased awareness of system limitations and errors. This result challenges conventional assumptions of TAM and points to the importance of perceived system quality and user expectations. The theoretical contribution of the research is that it extends the TAM model to sustainable infrastructures and the refinment of the model's assumptions with novel variables. At a practical level, it highlights that encouraging technology use requires the combined management of complex, individual and social factors. The findings may inform both policymakers and system operators in designing more user-centered and trust-enhancing circular economy systems. There is also a need to implement a better DRS to support integrated strategies that address individual motivations, social dynamics, and communication design.

1 | Introduction

The management of plastic waste is one of the most challenging and pressing environmental issues nowadays. The annual production of plastics exceeds 350 million tons (Statista 2025), a significant portion of which ends up in the natural environment due to improper waste management. The existence of microplastics causes risks not only to local ecosystems but also to human health (Li et al. 2023). This growing issue has been recognized globally. For instance, The European Union introduced its Waste Framework Directive in 2008, which has since undergone several amendments. One of the most significant revisions occurred in 2019 with the adoption of the Single-Use Plastics Directive (SUP) to improve recycling efficiency and reduce the impact of plastic waste (European Commission 2021). A key element of the updated regulation is the requirement for Member States to implement deposit-refund systems (DRS) for plastic and glass beverage containers. This could ensure that appropriate return infrastructure is made available. Despite such initiatives, inadequate waste handling and low recycling rates remain global problems (Kolluru and Raja 2025; Okori et al. 2024). One of the primary challenges is the inefficiency of source-level waste segregation. Numerous studies (see e.g., Ibáñez-Forés et al. 2018; Oliya et al. 2024; Teixeira et al. 2014) have shown that conscious and effective selective collection significantly contributes to reducing environmental burdens. Properly sorted plastic waste reduces processing costs, increases the proportion of recyclable materials, and supports the realization of circular economy principles (Babaremu et al. 2022; Payne et al. 2019).

Shanmugaraja et al. (2024) emphasize the important role of emerging technologies in plastic waste management. Particularly promising are automated DRS, such as the REpont initiative introduced in Hungary which was launched in mid-2024 as part of the national waste management concession. The objective of this mandatory DRS is to ensure that within 3 years, at least 90% of plastic and glass bottle packaging under the regulation will be returned (Ráti and Maró 2026). However, the implementation of this system has faced many challenges. According to a recent survey (Publicus 2024), 47% of participants who attempted to use the system encountered some form of difficulty, and only 32% believed that the new deposit system is an effective method to promote the reuse of beverage containers. The effectiveness of the REpont system is also influenced by consumer participation and behavior (Feng et al. 2017; Khan et al. 2019; Zhao et al. 2014). While existing infrastructure is important, the willingness of consumers to collect and return empty bottles is also essential. This requires trust in the system and its integration into daily routines. However, the factors that most strongly influence positive waste-handling attitudes and behaviors are not self-evident. To understand these factors, a well-structured analytical framework is required. To explore the mechanisms influencing behavior, an extended and customized version of the Technology Acceptance Model (TAM) is applied in this study. TAM is a well-established and reliable model that is not only particularly suitable for studying the acceptance of new technologies (Fayad and Paper 2015; King and He 2006), but also sufficiently flexible to allow the integration of new factors.

The novelty of this research lies in the integration of recycling- and sustainability-related factors, such as environmental awareness, social pressure, and financial incentives into the framework of the TAM. The inclusion of environmental consciousness is supported by prior findings that highlight its importance in recycling and circular consumption behavior (e.g., Kautish et al. 2019; Kim and Lee 2023). Social norms and pressure have been identified as a strong determinant of pro-environmental practices, including participation in return schemes (Graf et al. 2023; Shah and Yang 2023). Financial incentives have been shown to be effective in motivating sustainable behavior, especially when combined with normative messaging (Burtch et al. 2018; Picuno et al. 2025). Furthermore, access to clear and reliable information is critical for the correct use of novel infrastructures (Martinho et al. 2024). By extending TAM with contextually relevant constructs, this study provides a novel framework for understanding consumer acceptance of physical DRS infrastructures in the circular economy.

This was analyzed using partial least squares structural equation modeling (PLS-SEM), resulting in a comprehensive model which addresses the complexity of sustainable technology acceptance. This approach not only extends the existing literature on the topic (Pereira et al. 2024), but is also relevant from a practical point of view, as it may offer recommendations for promoting the widespread adoption and effectiveness of different waste management technologies. Furthermore, this study is one of the first to empirically examine a DRS through the lens of TAM, while also quantifying the gap between behavioral intention (BI) and actual use. By incorporating contextual moderators (e.g., presence of children and perceived information quality), the model captures critical determinants of technology uptake in real-world sustainability initiatives. While TAM has been extensively applied to digital platforms and e-services (Ahn et al. 2016; Biswas and Roy 2018), to our knowledge it has not yet been used to study physical deposit-refund infrastructures. This represents an important theoretical contribution, as consumer acceptance of tangible infrastructures may involve different drivers compared to digital contexts.

Furthermore, this study makes several important contributions to the literature on technology acceptance and sustainability. First, it is among the very few empirical investigations that apply an extended TAM specifically to a DRS targeting plastic waste, an area that remains largely underexplored in the academic domain. While TAM has been validated in numerous technological contexts (Borges and Kubiak 2016; Davis et al. 1989; Liu et al. 2010; Muñoz-Leiva et al. 2017), its application to selective waste return systems, involving physical interactions and behavioral feedbacks, represents a novel theoretical advancement. Second, the model integrates psychological, social, informational, and economic dimensions into the classical TAM framework. Thus, the research offers a multidimensional approach capable of addressing the complexity of sustainable technology acceptance. Third, the model does not merely stop at behavioral intention, as most TAM-based studies do, but explicitly measures and models actual system usage. This allows for a better understanding of the frequently overlooked gap between intention and behavior (Sheeran 2002), a crucial distinction for system operators and policymakers aiming to increase system adoption.

Finally, by testing moderating effects—i.e., the presence of children or information quality, this study adds better understanding of contextual influences in sustainability-oriented technology uptake. Beyond its theoretical contribution, this study also has important practical implications. Understanding the behavioral drivers of DRS acceptance is essential for policymakers and system operators aiming to increase return rates and ensure the long-term effectiveness of circular economy infrastructures. By identifying the relative importance of perceived usefulness, social norms, and financial incentives, the findings provide evidence-based guidance for designing more user-centred, accessible, and socially acceptable DRS. The success of such systems depends not only on regulatory design but also on consumer acceptance and everyday behavioral engagement. In this way, the research contributes not only to theory development but also to the improvement of real-world sustainability interventions.

To address the identified gaps and to achieve these contributions, this study is guided by the following research question: What factors influence the BI and actual use of a national DRS when analyzed through an extended TAM framework? More specifically, the study seeks to examine: (1) how perceived usefulness (PU) and perceived ease of use (PEOU) shape behavioral intention; (2) how environmental consciousness and social pressure contribute to technology acceptance; (3) whether financial incentives directly influence actual system use; and (4) to what extent an intention–behavior gap exists in the context of a mandatory DRS. To do so, the remainder of the paper is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 presents the data collection process and methodological approach. Section 4 reports the empirical results and hypothesis testing. Section 5 discusses the theoretical, managerial, and policy implications, as well as the limitations of the study. Finally, Section 6 concludes.

2 | Literature Review

2.1 | The Connection Between the Acceptance of Technology and Sustainability

Technology and technological advancement are considered crucial in addressing sustainability, especially in waste management and sustainable development (Arora et al. 2018; Youssef et al. 2018). Advanced recycling technologies (e.g., automated sorting systems and waste-to-energy processes) have been shown to significantly improve recycling rates and reduce the volume of waste (Devi et al. 2024; Khan et al. 2022; Prajapati et al. 2021; Pratap et al. 2021). Furthermore, Webersik and Wilson (2009) have supported the integration of technological solutions into economic development strategies to promote growth—while minimizing environmental damage. Nevertheless, resistance to new technologies or hesitancy in adopting them may be encountered. A lack of trust in developers or service providers can exacerbate this reluctance. Additionally, limited technological literacy and the perceived complexity of new systems may act as barriers. If consumers do not perceive a clear necessity for technology or have had negative experiences with previous innovations, they are less likely to adopt it, which in turn reduces and weakens the effectiveness of the new solution (Al-Emran and Griffy-Brown 2023; Benamati and Serva 2007; Parente and Prescott 1994; Shoabjareh et al. 2024).

Numerous theoretical models have been developed to explain the factors influencing the acceptance and use of new technologies. Among these, one of the most prominent is the TAM (Davis 1985; Davis et al. 1989). Based on BI, PU, and PEOU, TAM has served as a robust framework for predicting user behavior and has proven applicable across various contexts (Borges and Kubiak 2016; Liu et al. 2010; Muñoz-Leiva et al. 2017). TAM suggests that individuals' BI to use technology is significantly influenced by their PU and PEOU (Wilson and Lankton 2004). According to Davis et al. (1989), PU reflects the extent to which a person believes that using a particular system would enhance their job performance. In contrast, PEOU estimates the degree to which an individual believes that using the system would be free of effort. These two factors are assumed to be interrelated: the easier technology is to use, the more valuable it is perceived to be.

While TAM has demonstrated strong predictive power across various technological contexts, its original formulation focuses primarily on cognitive evaluations of PU and PEOU. However, in the case of environmentally friendly technologies, these two dimensions alone may not sufficiently explain user acceptance. Prior research indicates that additional factors, such as environmental attitudes, trust in public institutions, and climate-related skepticism, can significantly shape individuals' willingness to adopt green technologies, even when such systems are perceived as useful and easy to operate (Al-Emran and Griffy-Brown 2023; Feng et al. 2017; Shoabjareh et al. 2024). The original TAM emphasizes cognitive assessments; however, sustainability-oriented systems such as DRS operate within a broader socio-environmental context. In such cases, user decisions are shaped not only by instrumental evaluations but also by value orientations, perceived social expectations, and contextual economic incentives (Ajzen 1991; Bamberg and Möser 2007; Steg and Vlek 2009). Therefore, extending TAM with environmental, normative, and contextual variables is theoretically justified in order to capture the multidimensional determinants of DRS adoption (Yuriev et al. 2020).

The gap between the intention to use technology and actual behavior also needs to be highlighted. Thus, supplementing the classic TAM model with social and attitudinal dimensions is essential for a deeper understanding of the adoption of sustainability-related technologies. Behavioral intention, although a strong predictor of use, does not automatically translate into consistent action (Feil et al. 2023; Sheeran 2002; Webb and Sheeran 2006). Especially in sustainability contexts, practical constraints, situational factors, or motivational inconsistencies may weaken the intention–behavior link (Carrington et al. 2010; Kollmuss and Agyeman 2002).

This notion has been supported by studies in the domain of information technology adoption, which suggest, for example, that systems perceived as easy to use are more readily engaged with by users, thereby enhancing their acceptance (Purwanto and Budiman 2020). Thus, PEOU functions as an anticipatory process, while PU emerges as the outcome of such expectations (Sun and Rau 2015). A comprehensive literature review by Marangunić and Granić (2015) spanning the period from TAM's inception in 1986 to the 2010s highlights its effectiveness in predicting user acceptance of new technologies. However, they also emphasize that while TAM has been validated in many contexts, future research may benefit from exploring more complex models and integrating TAM to capture the full range of factors influencing technology acceptance. Similar conclusions have been drawn by numerous authors (Al-Adwan 2020; Chau 1996; Gupta 2020; Holden and Karsh 2010), who recommend extensions of the model to account for additional influential factors such as social influence and voluntariness. Other research (FakhrHosseini et al. 2024; Matemba et al. 2020; Sohn and Kwon 2020) has emphasized the importance of user trust and concerns about data privacy, proposing the inclusion of constructs such as trust, perceived risk, and user experience.

However, TAM is not only indirectly applicable to sustainability research. It has been widely adapted and expanded to examine the adoption of various sustainability-related technologies, including renewable energy systems, green transportation solutions, smart home devices, digital education platforms, and circular economy tools such as e-waste recycling and eco-labels (Table 1). As a result, TAM has become an established tool for understanding the adoption of sustainable technologies. But its application to DRS remains unexplored, while consumers may still reject even simple innovations—such as LED bulbs with green labels (Yokessa and Marette 2019)—due to skepticism about sustainability and climate change. This study addresses this gap by employing an extended TAM framework that not only integrates various sustainability factors (environmental awareness, social pressure) but also considers demographic, economic, and informational factors to empirically examine the acceptance and BI related to the REpont DRS system in Hungary, an app- and machine-based infrastructure incentivizing bottle returns through monetary refunds.

2.2 | Formatting the Hypothesis

Based on the integrated theoretical framework and the unique features of the REpont system, the following hypotheses are proposed. Pro-environmental values and normative expectations from one's social environment can shape both the way people evaluate the system's utility and their willingness to engage with it. Individuals who are environmentally conscious may perceive the REpont system as a meaningful contribution to sustainability goals (Khan et al. 2019; Zhao et al. 2014). Environmental consciousness is conceptualized as a value-based orientation reflecting the perceived personal importance of environmental protection and recycling. Individuals with stronger pro-environmental values are more likely to interpret sustainability-oriented systems as meaningful and beneficial (Bamberg and Möser 2007). In this sense, environmental consciousness functions as a cognitive framing mechanism that biases evaluative judgment toward perceiving the system's environmental utility as personally relevant, thereby strengthening PU even before practical experience occurs. Information availability may function as a cognitive boundary condition. Higher perceived knowledge increases evaluative confidence, which in turn strengthens the consistency between PU and behavioral intention. In contrast, limited information may weaken this translation due to uncertainty or ambivalence.

At the same time, perceived social expectations—such as the influence of peers, family members, or community norms—can reinforce the intention to use the system, independently of technical considerations (Feng et al. 2017; Prajapati et al. 2021). Perceived social pressure is defined as subjective normative influence, reflecting the extent to which individuals perceive that significant others expect them to engage in a given behavior (Helferich et al. 2023; Rivis and Sheeran 2003). In the context of the REpont system, it captures socially reinforced expectations related to bottle return participation. Environmental consciousness is expected to influence PU by shaping the evaluative framework through which the system is interpreted (Bamberg and Möser 2007). In parallel, perceived social pressure operates through normative mechanisms, reinforcing behavioral intention by activating conformity motives and internalized social expectations (Helferich et al. 2023). Such normative cues can directly shape intention even when cognitive assessments (e.g., usefulness) are only moderately favorable.

However, prior empirical findings regarding the strength of normative influence are not fully consistent. While several studies show a strong and direct effect of subjective norms on behavioral intention (Dong et al. 2022; Yang et al. 2021), other research suggests that social norms may exert only indirect or context-dependent effects, primarily shaping attitudes or PU rather than intention itself (Holden and Karsh 2010). Moreover, when financial incentives or regulatory obligations are salient, the relative explanatory power of social norms may diminish (Burtch et al. 2018; Graf-Vlachy et al. 2018). These inconsistencies indicate that the influence of perceived social pressure may vary depending on the institutional and motivational environment in which adoption occurs. In mandatory, incentive-based systems such as DRS, normative mechanisms may operate differently compared to voluntary digital or green consumption cases.

Hypothesis 1. *Environmental consciousness and perceived social pressure both positively influence the PU of the REpont system and strengthen BI to use it.*

While environmental and normative motives may shape intention, financial incentives such as the HUF 50 monetary refund associated with bottle returns are expected to directly drive action. Financial incentives are conceptualized as external economic motivators that provide tangible rewards for engaging in a given behavior. Unlike attitudinal or normative determinants, financial incentives operate through direct economic motivation (Andrzej Lipinski et al. 2025). Even in the absence of strong pro-environmental beliefs or social pressure, the prospect of tangible financial return can be sufficient to prompt users to participate in the system (Borges and Kubiak 2016; Yokessa and Marette 2019). This suggests a dual-motivation structure within the extended TAM. While attitudinal and normative constructs operate through internalized value-based pathways, financial incentives activate behavior through an external, outcome-driven mechanism that bypasses intention formation and directly influences action.

Hypothesis 2. *Financial incentives positively influence actual use of the REpont system, regardless of attitudinal or normative factors.*

Individuals raising children may attribute additional value to the REpont system due to its educational or financial appeal. Parental status may strengthen the motivational relevance of sustainability-oriented systems (Lawson et al. 2019). Individuals raising children may assign greater long-term environmental significance to recycling behavior due to intergenerational responsibility considerations. In this sense, having children may amplify the relationship between PU and behavioral intention. In addition, bottle return activities can serve as an opportunity to involve children in sustainable practices or provide them with pocket money, thereby strengthening parents' perception of usefulness and increasing their behavioral commitment (Al-Emran and Griffy-Brown 2023; Zhao et al. 2014). Thus, parental status may operate as a value-salience amplifier. When individuals evaluate the usefulness of the REpont system, intergenerational considerations can heighten the perceived long-term significance of the behavior, thereby intensifying the attitude–intention linkage rather than directly increasing intention per se.

TABLE 1 | Overview of TAM applications in sustainable technology contexts.

Article	Technology	TAM version	Methodology	Category	Key limitation	Gap addressed
Ahn et al. (2016)	Smart thermostats, energy monitors	Sustainable household TAM	Quantitative survey, SEM	Smart home/energy	Voluntary digital adoption	Examines mandatory physical infrastructure
Biswas and Roy (2018)	Green products/apps	TAM	Quantitative survey, SEM	Sustainable consumption	Focus on intention only	Models actual system use
Chen et al. (2017)	Smart meters	TAM/SETAM	Quantitative survey, SEM	Smart energy	No financial incentive variable	Integrates direct financial incentives
Ma et al. (2017)	Sustainability labels (apps)	TAM	Quantitative, regression	Green consumption	No infrastructure-based system	Applies TAM to physical DRS infrastructure
Aboelmaged (2020)	E-waste recycling	Extended TAM + TPB + Habit	Quantitative survey, SEM	E-waste Management	Small, non-national sample	Nationally representative sample ($n = 1005$)
Anser et al. (2020)	Green tech in logistics	Energy-augmented TAM	Quantitative, conceptual model	Green logistics	No behavioral data	Includes behavioral intention & actual use
Yang et al. (2021)	Renewable energy tech	TAM + subjective norms	Quantitative survey, SEM	Renewable energy	Voluntary context	Tests norms in mandatory DRS
Dong et al. (2022)	Ecological farming tech	Integrated TAM + TPB	PLS-SEM	Agriculture/carbon	No financial incentive analysis	Compares normative vs. financial drivers
Papagiannidis and Marikyan (2022)	Various digital tools	TAM framework	Conceptual analysis	Organizational sustainability	No empirical testing	Large-scale empirical validation
Rosli et al. (2022)	E-learning systems (COVID-19)	TAM	Literature review	Education/ sustainability	No behavioral modeling	Models intention–behavior gap
Nag and Mehendale (2023)	Hybrid cars	TAM + TPB	Quantitative survey, SEM	Sustainable mobility	No infrastructure analysis	Applies TAM to circular infrastructure
Oguntuase et al. (2023)	Low-carbon technologies	Bioeconomy TAM	SEM + validation	Bioeconomy/ Low-carbon	Voluntary tech adoption	Mandatory national DRS
Wong et al. (2024)	Renewable energy	TAM + TPB	SEM	Renewable energy	No contextual moderators	Includes moderators (children, information)

Hypothesis 3. *Having children increases BI to use the REpont system.*

Intentions do not always translate into concrete action. Despite favorable attitudes or intentions, practical constraints, inconvenience, or situational factors may prevent users from engaging with the system as often as they planned (Davis et al. 1989; Muñoz-Leiva et al. 2017; Sun and Rau 2015). The intention–behavior gap may emerge when situational constraints, habit strength, or motivational inconsistencies weaken the translation of favorable intentions into actual behavior. Examining this discrepancy allows for a more realistic assessment of system adoption beyond declared willingness to use the technology. Investigating this intention–behavior gap is therefore essential to understanding real-world system adoption.

Hypothesis 4. *There is a measurable gap between BI and actual use of the REpont system.*

Based on the above, extending TAM in the context of DRS is theoretically justified by the need to integrate environmental value orientations, normative influences, and contextual motivators into the traditional cognitive framework of usefulness and ease of use (Helferich et al. 2023; Youssef et al. 2018; Yuriev et al. 2020). To test the hypothesis, this study uniquely applies an extended TAM model to the context of a DRS. The model not only integrates various sustainability-related factors (e.g., environmental awareness and social pressure) but also incorporates demographic, economic, and informational variables, reflecting evidence that financial and contextual moderators shape pro-environmental behavioral outcomes (e.g., Xu et al. 2023). Furthermore, it examines the relationship between BI and actual behavior to understand consumer engagement in sustainable waste management technologies, acknowledging that social and structural influences can condition the translation of intention into action (Grønhøj and Thøgersen 2012; Lawson et al. 2019).

3 | Materials and Methods

3.1 | Presentation of the Questionnaire and Sample

The analysis was based on a questionnaire survey developed in accordance with the relevant literature (Chen et al. 2017; Dong et al. 2022; Ráti et al. 2024; Venkatesh and Davis 2000) and established methodological standards. These sources provide the conceptual foundation for the TAM, including its core constructs as well as a basis for integrating context-specific extensions such as environmental consciousness, financial incentives, and social pressure. Data were collected through an anonymous online questionnaire survey designed to explore attitudes and behavioral patterns related to the DRS. The survey was shared in public social media groups with at least 1000 members with a regional or municipality-specific focus to reach a socially diverse sample with particular attention to gender, age, and place of residence. Social media-based data collection is widely recognized as a suitable method for investigating social phenomena that require broad population participation (Fricker 2008; Kosinski et al. 2015; Whitaker et al. 2017). Throughout the process, internationally accepted methodological practices for social media research were followed (Fricker 2008; Kosinski et al. 2015). Participation was voluntary, and detailed information about data privacy and protection, and research objectives was provided at the beginning of the survey.

Data collection was conducted between September 24 and December 24, 2024. The questionnaire consisted of several thematic blocks covering environmental attitudes, recycling-related perceptions, REpont-specific TAM constructs, and sociodemographic variables. All attitudinal measures were assessed using 5-point Likert-type scales. To approximate national demographic proportions, targeted sampling by gender, age, and region was implemented. Quota thresholds (see in Table 2) were predefined using official 2024 population statistics published by the Hungarian Central Statistical Office (KSH). During the data-collection period, the distribution of incoming responses was continuously monitored. Once the required number of respondents within a given demographic cell (defined by gender, age group, and region) had been reached, additional responses from that category were no longer included in the analytical dataset. This quota-based procedure was intended to approximate national population proportions within the limitations of voluntary online participation.

Data quality was ensured through several predefined criteria. Incomplete questionnaires were removed, as were cases exhibiting straight-lining (identical responses across all items), and deliberately nonsensical demographic answers (e.g., unrealistic age or random strings). Furthermore, responses completed in an unrealistically short time, below the predefined minimum threshold, were excluded, as they indicated insufficient engagement with the questionnaire. After applying these quality filters and retaining only respondents who fulfilled the predefined demographic quota requirements for gender, age group, and region, the final analytical sample consisted of 1005 respondents. In line with contemporary PLS-SEM guidelines, minimum sample size requirements were evaluated using more precise approaches proposed by Kock and Hadaya (2018), including the inverse square root and gamma-exponential methods. Based on these criteria, the final sample of 1005 respondents substantially exceeds the recommended thresholds, ensuring stable parameter estimation and sufficient statistical power.

3.2 | Methods and Models Used

To analyze the data, structural equation modeling was applied using the variance-based partial least squares (PLS) method, implemented in R. This approach is particularly suitable for TAM-based models using Likert-scale data and does not require the assumption of normal distribution (Haenlein and Kaplan 2004; Henseler et al. 2015). Compared to conventional TAM applications, the present model includes the traditional PU and PEOU dimensions, as well as additional reflective constructs relevant to the DRS context, including environmental consciousness and perceived social pressure. The model also incorporates observed contextual variables such as information availability, parental status, and financial incentives.

Building on this extended conceptual framework, the model combines adapted and original scale items. The constructs of

TABLE 2 | Presentation of the sample.

Characteristic	Respondents ($n = 1005$)	Respondents (%)	Hungarian population (%)
Gender			
Male	469	47%	47%
Female	536	53%	53%
Age			
18–29	160	16%	16%
30–39	161	16%	16%
40–59	374	37%	37%
60+	310	31%	31%
Region			
Central Hungary	319	32%	32%
Central Transdanubia	112	11%	11%
Western Transdanubia	102	10%	10%
Southern Transdanubia	90	9%	9%
Northern Hungary	111	11%	11%
Northern Great Plain	150	15%	15%
Southern Great Plain	121	12%	12%

PU, PEOU, and BI were developed based on established TAM literature (Davis 1985; Venkatesh and Davis 2000), but were contextually adjusted to reflect the specific functions and user experience of the REpont system. Since no prior TAM-based studies have developed or validated measurement scales specifically for DRS, the constructs of environmental consciousness and social pressure were operationalized using original items tailored to the REpont system. These were grounded in relevant sustainability literature (Rosli et al. 2022) and adapted to reflect the unique characteristics of the implementation. In contrast, financial incentives and actual use were specified as observed single-indicator variables rather than reflective latent constructs. Financial incentives refer to a clearly defined monetary refund (HUF 50), while actual use captures self-reported behavioral frequency. Given their concrete and unidimensional nature, single-item measurement was considered methodologically appropriate (Diamantopoulos et al. 2012; Hair et al. 2021a). The development of these items was necessary to adequately capture the socio-technical environment of the system and the influence of motivators such as the HUF 50 refund on recycling behavior. The full list of scale items and variable operationalization is provided in Table 3.

In addition to the model's core constructs, two moderating variables were tested: having children and access to information. Information availability was specified as a single-item observed moderator capturing respondents' perceived level of system-related knowledge. Having children was measured as a binary (yes/no) variable indicating whether the respondent has at least one child under the age of 14 in the household. Neither represents an internal psychological determinant of technology acceptance. Rather, they capture external, contextual, and demographic conditions. Furthermore, the model explicitly addresses the frequently observed discrepancy between BI and actual use (e.g., Bhattacherjee and Hikmet 2007; Sheeran 2002). This gap is formally incorporated into the extended framework to test the hypothesis that users may express willingness to use the REpont system without necessarily engaging in consistent return behavior. The final model structure reflects these considerations and is presented in Figure 1.

3.3 | Validation of the PLS-SEM Model

In the PLS-SEM modeling process, the following steps were carried out: (1) Analysis of the core dimensions of the original TAM; (2) Integration of additional constructs into the model, including environmental consciousness, social pressure, information availability, and financial incentives; (3) Specification of the relationships between latent variables and their measurement indicators (outer model), as well as the regression paths between the latent constructs and observed variables within the structural model (inner model).

This approach allows a deeper understanding of the factors influencing the acceptance of novel technology, particularly from the perspective of pro-environmental behavior and individual attitudes. The results contribute to identifying key elements that can enhance the effectiveness and acceptance of recycling technologies. The validation of the outer model was conducted using standard reliability and validity criteria. Internal consistency was assessed through Cronbach's alpha and composite reliability scores (Hair et al. 2010). Convergent validity was evaluated based on the outer loadings and average variance extracted (AVE) for each construct (Hair et al. 2010; Hair et al. 2021b). As shown in Table 4, all reflective multi-item constructs exceeded

TABLE 3 | Scale items and variables.

Construct	Item	Code	Supporting literature
Perceived usefulness (PU)	Using the REpont system is a good solution for managing bottle returns.	q1	(Bamberg and Möser 2007; Davis et al. 1989)
	I believe that using the REpont system is beneficial for the environment.	q2	
	The REpont system helps me manage plastic and glass waste more efficiently.	q3	
	Using the REpont system makes recycling easier for me.	q4	
Perceived ease of use (PEOU)	I find the REpont system user-friendly.	q5	(Davis et al. 1989)
	It is easy to learn how to use the REpont system.	q6	
	Using the REpont system was simple and convenient.	q7	
Behavioral intention (BI)	I will recommend the REpont system to others.	q8	(Ajzen 1991; Yuriev et al. 2020)
	I am willing to change my daily habits in order to use the REpont system.	q9	
	I will download and use the REpont app.	q10	
	I will regularly use the REpont system.	q11	
Environmental consciousness	How important do you consider recycling?	q12	(Bamberg and Möser 2007; Stern 2000)
	Recycling is an important value for me.	q13	
	I would use the REpont system even without financial incentives.	q14	
	I consider it important to participate in selective waste collection to protect the environment.	q15	
Social pressure	People who are important to me think I should use the REpont system.	q16	(Helferich et al. 2023; Rivis and Sheeran 2003)
	I feel a social obligation to participate in recycling.	q17	
Financial incentives	The 50 HUF refund motivates me to use the REpont system.	q18	(Gneezy et al. 2011; Thøgersen 2003; Xu et al. 2023)
Actual use	How often do you use the REpont system to return bottles?	q19	(Thøgersen 2003; Yuriev et al. 2020)
Information	Have you been properly informed about how to use the REpont system?	q20	(Rivis and Sheeran 2003; Yuriev et al. 2020)

the recommended threshold of 0.70 on each of these measures, indicating high reliability and confirming stable internal consistency across all reflective constructs. Convergent validity was confirmed by AVE scores, all of which surpassed the 0.50 cutoff. The AVE values ranged from 0.528 (BI) to 0.815 (social pressure), indicating that a substantial proportion of the indicators' variance was captured by their respective latent constructs.

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). In the Fornell–Larcker test, the square root of the AVE for each construct exceeded its correlations with all other constructs, confirming adequate discriminant validity. The HTMT values were also evaluated and found to be below the recommended threshold of 0.90 in all cases, supporting discriminant validity. In addition, 95% bias-corrected and accelerated (BCa) confidence intervals were computed using bootstrapping with 5000 subsamples. The upper bounds of the confidence intervals for all HTMT values remained below 1.00, confirming also the robustness of the results (Table 5). These findings validate that each reflective latent construct captures a distinct theoretical concept within the measurement model.

To assess potential common method bias, two complementary statistical procedures were applied. First, the full collinearity VIF approach proposed by Kock (2015) was used. All variance inflation factor (VIF) values for the structural predictors were below the conservative threshold of 3.3, indicating that common method variance is unlikely to bias the results. Second, Harman's single-factor test was conducted using exploratory factor analysis (Podsakoff et al. 2003). The first unrotated factor accounted for 45.03% of the total variance, which is below the

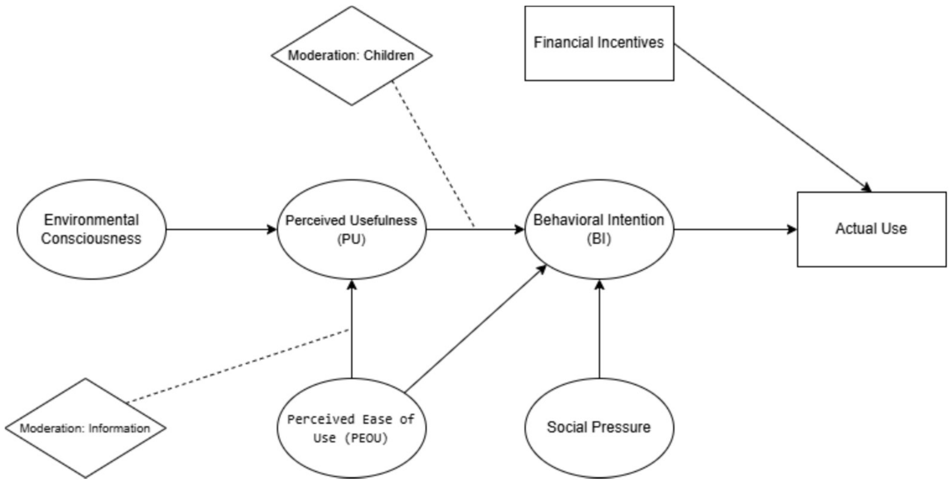

FIGURE 1 | The extended TAM-model.

TABLE 4 | Reliability and convergent validity of constructs.

Construct	Cronbach's alpha	rhoC	AVE	rhoA
PU (perceived usefulness)	0.897	0.897	0.685	0.898
PEOU (perceived ease of use)	0.866	0.867	0.686	0.873
Environmental consciousness	0.830	0.827	0.548	0.836
Social pressure	0.894	0.898	0.815	0.905
BI (behavioral intention)	0.812	0.813	0.528	0.836

TABLE 5 | Summary of discriminant validity.

Construct pair	Fornell–Larcker criterion	HTMT ratio <0.90	HTMT CI upper bound <1.00
PEOU—PU	0.829 > 0.789	0.891	0.915
PU—BI	0.828 > 0.765	0.874	0.902
Environmental_ Consciousness—PU	0.740 > 0.606	0.695	0.739
Social_Pressure—BI	0.726 > 0.645	0.735	0.776
BI—Actual_Use	0.726 > 0.480	0.526	0.573

Note: Fornell–Larcker criterion: The square root of AVE must be greater than 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.

commonly accepted 50% threshold. These results suggest that common method bias does not pose a serious threat to the validity of the findings. The inner model was assessed by examining the path coefficients (β-values) between latent constructs and the explained variance (R^2) of endogenous variables (Chin 1998; Hair et al. 2010). The model's predictive relevance was further confirmed using the Stone–Geisser Q^2 criterion, which yielded positive values.

4 | Results

4.1 | Results of the Structural Model

The evaluation of the structural model aimed to statistically confirm the hypothesized relationships between constructs. Model fit and predictive capability were assessed based on direct effects (path coefficients), explained variance (R^2), and total effects. Each hypothesized relationship in the conceptual model, including moderating effects, was examined (Table 6). PEOU exerted a strong and statistically significant positive effect on PU ($\beta=0.742$, 95% CI [0.684, 0.817]), confirming a core relationship in the technology acceptance framework. However, the direct effect of PEOU on BI was not significant ($\beta=0.079$, CI [−0.113, 0.247]), suggesting that PEOU may influence user intentions primarily through its effect on PU. PU had a strong and significant direct effect on BI ($\beta=0.620$, CI [0.437, 0.834]), while social pressure also significantly influenced BI ($\beta=0.307$, CI [0.225, 0.386]).

These findings underscore the role of both individual cognitive assessments and external normative influences in shaping intentions to use the system. Environmental consciousness positively impacted PU ($\beta=0.279$, CI [0.208, 0.350]), indicating that individuals with stronger pro-environmental attitudes perceive the system as more beneficial. BI was the strongest predictor of actual use ($\beta=0.492$, CI [0.432, 0.549]), supporting the theoretical link between intention and behavior. Additionally, financial incentives showed a significant positive effect on actual use ($\beta=0.127$, CI [0.067, 0.184]), highlighting the role of tangible rewards in motivating user engagement. Interaction effects, such as PEOU × Information → PU ($\beta=0.013$, CI [−0.056, 0.037]) and PU × Children → BI ($\beta=0.013$, CI [−0.030, 0.054]), were not statistically significant, suggesting that neither the level of information nor parental status moderated these specific pathways.

TABLE 6 | Results of the structural model.

Construct	R^2	Path coefficient (β)	T statistic	Confidence interval (95%)
Behavioral intention (BI)	0.838	PU → BI: 0.620	6.171	[0.437, 0.834]
Perceived usefulness (PU)	0.845	PEOU → PU: 0.742	22.238	[0.684, 0.817]
Actual use	0.291	BI → Actual Use: 0.492	16.461	[0.432, 0.549]
Environmental Consciousness → PU	—	Environmental_ Consciousness → PU: 0.276	7.634	[0.208, 0.350]
Financial incentives → Actual use	—	Finance → Actual Use: 0.127	8.040	[0.067, 0.184]
Social pressure → BI	—	Social_Pressure → BI: 0.307	7.520	[0.225, 0.386]
Interaction (PEOU*Information) → PU	—	PEOU*Information → PU: 0.012	0.384	[−0.056, 0.037]
Interaction (PU*Children) → BI	—	PU*Children → BI: 0.013	0.135	[−0.034, 0.050]

The model's explained variance was satisfactory. Specifically, PU was explained at 68.5% ($R^2 = 0.685$) by PEOU and environmental consciousness; BI at 75% ($R^2 = 0.750$) by PU and social pressure; and actual use at 42% ($R^2 = 0.420$) by BI and financial incentives. These R^2 values confirm strong predictive power, particularly for the intention to use the REpont system. Analysis of total effects revealed meaningful indirect pathways. Notably, the effect of PEOU on BI was primarily mediated through PU (total effect: $\beta = 0.543$, CI [0.473, 0.618]). Similarly, PU had a significant total effect on actual use ($\beta = 0.305$, CI [0.210, 0.417]), reinforcing its central role as a mediating construct between attitudes and behavior. Finally, indicator contributions were evaluated. All reflective items showed loadings above the 0.70 threshold, except for one item within BI (q10: 0.522), which was retained due to its theoretical relevance. Financial incentives, information availability, and actual use were modeled as observed single-indicator variables. Accordingly, indicator weights were not estimated for these variables, and their effects were evaluated directly within the structural model. The extended TAM-model and its values can be seen in Appendix 1.

4.2 | Hypothesis Testing

The study proposed four main hypotheses based on the extended TAM and contextual factors specific to the REpont system. The results of the PLS-SEM model provide varying degrees of support for these hypotheses (Table 7). The findings partially support our first hypothesis (*Hypothesis 1. Environmental consciousness and perceived social pressure both positively influence the PU of the REpont system and strengthen BI to use it*). Environmental consciousness had a statistically significant positive effect on PU ($\beta = 0.273$, $t = 7.435$, CI = [0.201, 0.343]), confirming the assumption that individuals with stronger pro-environmental values perceive the REpont system as more useful. Similarly, perceived social pressure had a strong and significant effect on BI ($\beta = 0.308$, $t = 7.521$, CI = [0.224, 0.385]). However, environmental consciousness had only a moderate effect on BI ($\beta = 0.167$), and its overall explanatory power was weaker. Still, the hypothesis is considered supported in principle, with the two antecedents acting on different endogenous constructs (PU and BI).

TABLE 7 | Summary of hypothesis testing.

Hypothesis	Statement	Result
Hypothesis 1	Environmental consciousness and social pressure influence PU and BI	Partially supported
Hypothesis 2	Financial incentives influence actual use	Supported
Hypothesis 3	Having children increases behavioral intention	Not supported
Hypothesis 4	There is an intention–behavior gap between BI and actual use	Supported

The second hypothesis (*Hypothesis 2. Financial incentives positively influence actual use of the REpont system, regardless of attitudinal or normative factors.*) was fully supported. Financial incentives had a direct and statistically significant effect on actual use ($\beta = 0.127$, $t = 4.979$, CI = [0.067, 0.184]), even though they did not significantly influence BI. This confirms that external motivators can drive action independently of cognitive or normative beliefs, emphasizing their role in converting intention into behavior. Contrary to expectations, the presence of children in the household did not significantly increase BI ($\beta = 0.021$, $t = 0.692$, CI = [−0.030, 0.075]). This result may be attributed to contextual barriers such as long waiting times, limited availability of machines, or a perceived lack of child-friendliness at return points. Therefore, the third hypothesis (*Hypothesis 3. Having children increases BI to use the REpont system.*) is not supported.

Finally, for the fourth hypothesis (*Hypothesis 4. There is a measurable gap between BI and actual use of the REpont system.*), the data suggest the presence of an intention–behavior gap. While BI significantly predicted actual use ($\beta = 0.492$, $t = 16.535$, CI = [0.432, 0.550]), the R^2 value for actual use remained relatively low ($R^2 = 0.291$). This indicates that while intention plays a role, other contextual or situational factors (e.g., convenience, physical access, and machine availability) may prevent users from acting on their intentions.

5 | Discussion and Implications

The results of the research confirm that TAM can be successfully applied to examine the acceptance of sustainability-oriented technologies, in this case of the DRS. While the TAM model has been widely used and validated in the field of information technology for decades (Davis 1985; King and He 2006; Marangunić and Granić 2015), its application to the physical infrastructure-based circular economy solutions has remained limited. This study aims to reduce this gap and at the same time highlight the combined role of both individual-level cognitive evaluations and broader social and contextual factors in the acceptance and actual use of the European DRS system.

The results show that PU of the system was the most important predictor of behavioral intention. This is consistent with previous TAM-based research (e.g., Purwanto and Budiman 2020; Liu et al. 2010) and supports that the subjective sense of the usefulness of the technology plays a central role in shaping user intention. However, PEOU only indirectly influenced intention through usefulness, which is consistent with Sun and Rau (2015) or Ma et al. (2017) conclusions that ease of use primarily increases the sense of the usefulness of the technology, rather than directly increasing the willingness to use and prompting behavioral engagement. This reinforces the original TAM's hierarchical structure and supports the importance of user-centered design in environmental technologies. The results also support that environmental awareness positively influences the PU of the system and has a moderate impact on intention to use. This is consistent with previous research (e.g., Khan et al. 2019; Zhao et al. 2014) that ecologically sensitive and environmentally motivated individuals are more likely to perceive the system as beneficial. However, the relatively weak direct effect on BI also indicates that attitudes alone are not sufficient to induce behavior, and practical incentives are also needed. Thus, there is a need to complement attitudinal predispositions with enabling conditions or incentives.

Social pressure was also found to be a strong influencer of behavioral intention, highlighting the role of normative influences described in sustainability-focused TAM extensions. This is supported by cross-sectoral findings from Dethier et al. (2025), who show that the influence of social norms and environmental awareness on sustainable behavior varies considerably across sectors such as mobility, clothing, and tooling. Their results underline the need for tailoring sustainability interventions to sector-specific motivational structures, which is in line with the contextual sensitivity of the REpont system. Moreover, previous findings (Dong et al. 2022; Yang et al. 2021) confirm that social norms and expectations often play a significant role in environmental behavior, especially when individual benefits are unclear. Interestingly, these normative factors influenced intention independently of cognitive assessments like perceived usefulness. It is in line with Feng et al. (2017) that community-based expectations function through distinct motivational channels. The study also highlights the unique and non-trivial role of financial incentives. The financial incentive—the 50 HUF deposit refund—directly and significantly influenced actual use but did not affect behavioral intention. This confirms previous findings (Borges and Kubiak 2016; Yokessa and Marette 2019) that financial motivations do not necessarily shape internal beliefs, but can be effective in activating or catalyzing behavior—especially when attitudes are ambivalent, or the environment is unsupportive. Thus, while cognitive and normative constructs explain why individuals intend to act, tangible incentives help bridge the intention–behavior gap.

The gap between intention and action (actual use)—the so-called intention–behavior gap (see e.g., Sheeran 2002)—was also evident and confirmed. Although intention to use significantly predicted use, the lower value of explained variance suggests that actual behavior may be constrained by additional factors (e.g., accessibility, convenience, availability of machines, time constraints, or user experience issues). Surprisingly, the presence of a child in the household was not a significant moderator, despite previous research suggesting that parents may be more committed to environmentally conscious behavior (Al-Emran and Griffy-Brown 2023; Zhao et al. 2014). This is likely due to the implementation challenges of the REpont system (e.g., lack of machines, long waiting times, non-child-friendly environment), which hinder families from actively using the system and prevent families from fully integrating return behavior into daily routines. Furthermore, the visible presence of homeless individuals collecting large volumes of bottles could create a socially uncomfortable atmosphere, and this situation could further discourage families, especially with young children, from treating bottle returns as a positive or shared experience. These finding are consistent with the criticisms raised by numerous studies (Al-Emran and Griffy-Brown 2023; Bhattacherjee and Hikmet 2007; Sheeran 2002) that TAM often underrepresents contextual barriers to capture real-world adoption patterns.

Overall, the research confirms the flexibility of the TAM model in examining sustainability technologies (Papagiannidis and Marikyan 2022) but also emphasizes the need to explain acceptance not only by individual attitudes. Thus, there is a need for multi-dimensional models that extend beyond individual perceptions. The integrated model developed here provides a more comprehensive picture of the social acceptance of environmentally friendly technologies and offers suggestions for increasing the effectiveness of DRS systems from a practical perspective. All of this is discussed in the next subchapter.

5.1 | Theoretical, Managerial, and Policy Implications

The study makes a significant theoretical contribution to the application of TAM in a sustainability-focused context, namely a nationwide DRS in Hungary. While the TAM model has been used widely and mainly to examine the acceptance of digital technologies, the present research adapts the model to a physical, infrastructural system by integrating constructs such as environmental awareness, social pressure, financial incentives, and informational factors. This integration confirms that TAM is applicable beyond digital environments and can be extended to systems where technology use is closely linked to behavioral change and collective action. The research also represents an important step in the theoretical modeling of the intention-behavior gap, which has long been a criticism of traditional TAM approaches (e.g., Al-Emran and Griffy-Brown 2023;

Sheeran 2002), enhancing the explanatory power of TAM in real-world environmental applications.

One of the most theoretically intriguing results is the negative effect of information on perceived usefulness. This "information paradox" may be interpreted as a cognitive dissonance between expected and actual system characteristics (Bhattacherjee 2001; Eppler and Mengis 2008). Users who reported being better informed perceived the REpont system as less useful, potentially because more information also revealed the system's flaws. Overexposure to information may also reduce novelty and diminish the perceived value of the system. This finding challenges the common assumption in TAM-based models that information availability uniformly enhances adoption and suggests the need for a more nuanced, possibly non-linear treatment of informational variables in future research. While the present study focuses on Hungary's DRS, the extended TAM framework proposed here has broader applicability to infrastructure-based sustainability systems. Many contemporary environmental policies rely on large-scale, system-level technological infrastructures, such as smart energy meters, pay-as-you-throw waste schemes, shared mobility platforms, or digital carbon-tracking applications, where adoption depends not only on PU and ease of use, but also on social norms, financial incentives, and informational environments (Hamari et al. 2016; Wolske et al. 2017). Theoretically, the findings suggest that multidimensional acceptance models may be particularly suitable for analyzing such hybrid policy-technological systems. In this sense, the study contributes not merely to DRS research, but to the broader theorization of sustainability-oriented technology acceptance.

From a managerial perspective, in terms of encouraging the use of the REpont system, the results make it clear that the perception of usefulness and alignment with community expectations are the main motivational drivers and factors for users. This suggests that system operators, service providers, and communication professionals should focus not only on functionality, but also on value- and norm-based messages. Improving the user experience (e.g., easy-to-use machines, smooth application experience, and interface) indirectly increases acceptance, even if it does not affect immediate behavioral intention. Financial incentives, although they do not strengthen intention, can trigger specific action, so it is worth focusing on the simplicity and reliability of reward mechanisms when designing the system. In addition, information availability and targeted communication towards specific groups (e.g., family members and elderly people) play a key role in building trust in the system. An important realization for management is that positive attitudes do not always automatically lead to actual use. To bridge this gap, physical barriers to the operation of the system—such as frequent machine breakdowns, long queues or complicated application registration—should and must be minimized. Previous studies (Johnson et al. 2016; Lidia et al. 2018) have highlighted that gamification and peer-based competitions are effective tools to strengthen recycling behaviors and long-term pro-environmental habits. Thus, at the same time, integrating elements of social experience and community-based (e.g., introducing "green challenges" or gamification), which can further increase social participation.

For policymakers, the results highlight that the introduction of a national sustainability technology, such as REpont DRS, is not just a technical or logistical issue, but also a process that requires social acceptance. To promote acceptance, regulation should encourage equity of access to the system (e.g., rural coverage and elderly-friendly locations) and promote information for different types of users, especially among groups with low technological affinity. The research suggests that the gap between intention and behavior could be narrowed by reducing physical barriers, such as improving the accessibility and operational stability of machines. Furthermore, strengthening environmentally-conscious behavior depends not only on individual but also on collective responsibility—this could be supported at the public policy level, for example through school education, campaigns, and community involvement (Maró et al. 2022; Schultz 2014; Yamin et al. 2019). Another important lesson is that financial incentives alone cannot establish a long-term impact. Monetary refunds can act as short-term behavioral activators, but to make the behavior sustainable, decision-makers need to take a greater role in reinforcing positive pro-environmental norms, increasing public trust, and creating a transparent and user-friendly regulatory environment.

Current conditions, such as long queues, frequent malfunctions, and the presence of social tensions around the machines (particularly the concentration of homeless individuals at some return points), make bottle returns an unattractive family activity. These tensions may stem from the system's technological limitations. REpont machines cannot issue cash refunds but instead provide store-specific vouchers that can only be redeemed at the same supermarket where the machine is located. This makes the vouchers less practical and encourages territorial use of machines by individuals who rely on the system for their livelihood. Thus, it would be advisable to establish return points that operate independently of specific retail chains, possibly near shelters or community centers, where they would not interfere with everyday shoppers. Such developments could help reduce pressure on high-traffic locations, make the system more socially acceptable, and create an environment in which individuals and families would feel more comfortable participating. In addition to highlighting factors that influence consumer acceptance, the findings also suggest that policymakers and system operators should address potential social tensions at return points and independent return stations. This can be mitigated by ensuring sufficient machine capacity and clear queue management, providing simple and accessible user guidance, and offering staff assistance during peak hours. Such measures can improve user experience, reduce conflicts, and enhance participation in the DRS.

6 | Conclusion

The study examined the acceptance and use of the DRS (in Hungary, the REpont system) introduced in the European Union through an extended version of the TAM, integrating environmental, social, informational, and financial predictors. A nationwide online survey was conducted to assess the influence of these factors. The results confirm that the PU of the system is the most important predictor of behavioral intention, while social pressure and environmental awareness also play a significant role. Furthermore, financial incentives directly influenced actual use of the system, while the information factor paradoxically had a negative effect on the perceived usefulness. These findings show that circular economy technologies require multidimensional acceptance models that integrate cognitive, social, and economic factors. The study offers several important contributions. First, it extends the applicability of TAM to infrastructural systems of the circular economy, an area that is still poorly explored in the literature. Second, it validates the extension of TAM to constructs such as environmental awareness and social norms and demonstrates their relevance in the acceptance of sustainability technologies. Third, it explores a theoretically intriguing phenomenon, the so-called "information paradox," according to which more information can reduce the perception of system usefulness.

The research has several limitations. First, the recruitment of participants through social media may involve potential self-selection biases. Individuals who are more digitally active or more environmentally conscious might have been more likely to participate. Similarly, voluntary participation may have attracted respondents already interested in recycling or circular economy initiatives, potentially inflating pro-environmental responses. Future studies should consider complementing social media recruitment with alternative sampling strategies (e.g., on-site surveys at return points and panel data) to mitigate these biases and increase generalizability. Furthermore, the cross-sectional design does not allow for causal inferences, and self-reported data may be biased by social expectations. Although the sample is representative of important sociodemographic aspects, changes over time (e.g., habituation and attrition) were not measured. In addition, the study focused on a specific national system (REpont) that was in the early phase of implementation, which may limit the generalizability of the results to other, more mature or differently structured redemption systems.

Overall, the results indicate that extended TAM models can serve as a general analytical framework for understanding behavioral adoption in infrastructure-based circular economy systems. By demonstrating how cognitive, social, informational, and economic dimensions interact, the study opens new opportunities for comparative research across sustainability technologies and supports more integrated policy design beyond the specific case of deposit-refund systems. Furthermore, this study demonstrates that the effectiveness of DRS depends not only on economic incentives but on how users cognitively and socially interpret the system. By advancing a multidimensional TAM extension, the research provides a clearer foundation for both theoretical development and evidence-based policy design.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request produced or examined.

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Appendix 1

The Extended TAM-Model With Values