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Investigating Residents' Acceptance of Mobile Apps for Household Recycling: A Case Study of New Jersey

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Abstract: Information Communication Technologies (ICTs) have created new opportunities to deliver recycling education. This study employs the Unified Theory of Acceptance and Use of Technology-2 (UTAUT-2) to examine primary factors impacting U.S. residents' intention to use recycling mobile applications. Uniquely, the research interrogates whether ICT adoption can increase the intention to recycle household waste and thus generate social change. The data, from an online survey of 1215 app users located in New Jersey, is analyzed using Partial Least Squares-Structural Equation Modelling (PLS-SEM). Results demonstrate that performance expectancy, facilitating conditions, hedonic motivation, and habit, have a positive and significant effect on the intention to use recycling apps. The intention to use apps also has a positive and significant effect on the intention to recycle. The results support the use of ICTs as a tool for building recycling habits. Recommendations for solid waste management practitioners, and app developers, are also discussed.

Keywords: ICTs; recycling; mobile apps; UTAUT-2; PLS-SEM

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1. Introduction

As the world population has risen, so has consumption; thus, sustainability continues to gain traction as a critical issue. The European Commission [1] predicts that the global consumer class will reach about 5 billion people by 2030, and thus the need for water, food, and energy, will increase respectively. Global waste will grow by 70% by 2050 unless precautions are taken [2]; as such, sustainability challenges will continue. The consumption cycle entails consumer waste: food, e-waste, plastic, etc. [3–5].

Recycling remains one of the most efficient and effective tactics to mitigate this environmental risk. Thanks to recycling, less waste goes to landfill or incineration. Recycling saves energy and lowers the necessity to collect raw natural materials like wood, minerals, and water [6]. Recycling even contributes to the economy; according to the REI report [7] (p. 1), it generated "681,000 jobs, $37.8 billion in wages, and $5.5 billion in tax revenue" in the U.S. in 2020.

Businesses are working to integrate better recycling practices, such as recyclable material development [8,9], application of recycled contents [10,11], and even moving to circular business models that eliminate waste [12–14]. This is important as the government pressure on recycling is increasing, with states starting to pass bills for extended producer responsibility programs [15]. For instance, Maine was the first American state to introduce the bill L.D. 1541, potentially reaching its full effect in 2024 [15,16]. The new law implies that local packaged goods manufacturers will provide funds for sustaining and developing municipal recycling programs. In particular, brands' financial contributions will depend on several characteristics of packaging: weight, recyclability, and clarity of disposal instructions. Waste management regulations in the U.S. vary from state to state; however, the overall tendency is that municipalities now carry the most responsibility and are looking to share it with producers [15].

One challenge in recycling is that despite the best efforts of municipalities, many residents in North America are recycling incorrectly. As of 2018, the recycling rate in the U.S. constituted 32.1%: Americans created 292.4 million tons of recyclable waste, out of which only 93.9 million tons ended up recycled or composted [17]. Recycling contamination is also an issue, costing municipalities millions of dollars a year and thus increasing taxes earmarked for waste collection [18,19]. Contamination occurs when garbage or non-recyclable material gets into the recycling system [18]. Cities with high contamination rates pay considerably more to support their recycling programs [18]. Globally, the standards for contamination in recycling are also becoming stricter. For example, in 2018, China (the biggest importer of recyclable waste in the world) banned the import of most plastics and raised the purity standards for other materials [19]. Given these challenges, recycling correctly is critical to ensuring this approach to waste management is effective.

Because residents are crucial stakeholders in the early stages of the recycling process, the success of community recycling programs largely depends on how well municipalities can communicate with residents and educate them on proper waste sorting. Recycling systems consist of several stages: sorting, collecting, and converting waste into new materials [20]. Thus, proper sorting is an integral part of a successful waste management system. However, several studies have indicated that the general public lacks knowledge of how to sort waste correctly [21–25]. Thus, educating citizens on waste sorting can decrease recycling contamination.

Investments in recycling education can also increase recycling rates [26]. The emergence of information and communication technologies (ICTs), such as mobile applications, has enabled innovation in various fields, including recycling education [27]. Hence, public administrations started placing high hopes on using novel electronic channels for information and service delivery [28]. ICTs can help consumers participate in recycling activities. However, research has shown that residents may struggle to accept and utilize ICTs to communicate with public administration [29].

Recent mobile technology research has used the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to evaluate ICTs and mainly focused on mobile apps facilitating language learning [30,31], fitness [32–34], banking [35,36], shopping [37–39], etc. However, the use of ICTs to promote socially responsible behaviors, like recycling, is less understood [40].

This study interrogates user acceptance of recycling apps using the UTAUT-2 framework. The research objective is to examine what factors positively affect the intention to use recycling applications. Studies of recycling ICTs adoption remain underrepresented in previously published literature, with a particular knowledge gap being the potential of green technology to increase recycling intentions in the North American context. This study strives to provide empirical insight, addressing this gap, and drive social change as a general outcome. Practical implications for recycling app development are also presented.

2. Theoretical Background

2.1. ICTs in Recycling

ICTs are widely used for municipal solid waste management: among other services, they supply content on proper waste sorting; send reminders about trash/recycling pickups; provide quick answers on what goes where if the user is unsure; quantify users' environmental impact; deliver up-to-date environmental news; show nearest recycling drop-off points; and even offer recipes that use leftover ingredients to decrease food waste [41].

There are local and global recycling apps. Examples of local apps are: Recycle Coach in the U.S. and Canada; Recycle Smart and Recycle Right in Australia; Recycle for Greater Manchester in the UK. Most of these allow users to input an address to inform users about local recycling standards, curbside collection schedules, and drop-off locations based on geolocation. An example of a global recycling app is My-Waste: it operates in different municipalities worldwide; full capabilities are available only for users whose municipality partners with the app [41].

Some previous studies explored the impact of ICTs in promoting recycling. In Singapore, scholars developed an application based on the RANAS (risks, attitudes, norms, abilities, and self-regulation) model to educate citizens on recycling and track their behavioral change [42]. Once the users accessed the app, they would receive stickers with QR codes, meant to be attached to the bags with recyclables. The bags would then end up in the sorting facility, and researchers would analyze and record the content of each pack and upload the results to the app [42]. The app quantified the individual users' impact on the environment and granted points that they could exchange for vouchers or monetary rewards. The experiment results demonstrated a boost in recycling rates from 20% to 40%, and a decline in contamination rates from 40% to 2% [42]. Another study, in Brazil, found that a mobile app helped improve the working conditions of recyclable waste pickers [43]. A recycling audit in Newark (NJ, U.S.) revealed that a recycling app reduced plastic bag contamination by 82% after a one-month teaching campaign [44]. Another audit of 60 households in Aurora (Ontario, Canada) indicated that after five educational campaigns delivered via the recycling app, the recycling contamination rate plummeted from 24.4% to 3.5% [45]. Aguiar-Castillo et al. [46] found that a gamified recycling app can foster tourists' recycling behavior in European cities.

Research demonstrates that gamified ICTs have been particularly useful in recycling education. Chin and Wahid [47] investigated the effect of a digital game on the recycling knowledge of 80 first-graders in Malaysia. The scholars tested two groups: the control group learned about recycling in a traditional method; and the intervention group used a gamified ICT. The intervention group demonstrated a considerable improvement in recycling knowledge compared to the control group [47]. Another study by Cheng et al. [48] aimed to inspect what factors affect the recycling intentions of young people after they had interacted with a gamified ICT. The focus group discussions revealed four primary factors driving recycling intention: "gameful experience, social influence, and intrinsic and extrinsic motivations" [48] (p. 1).

2.2. Technology Acceptance Models

The first technology adoption studies have used the technology acceptance model (TAM). The framework was used in the context of the users' performance at work and suggested that good UX design (i.e., "usable, useful, desirable, and credible" increases the likelihood of technology adoption) [49] (p. 2). The creators of this framework assumed that people make rational decisions and take the cost-benefit ratio into account [46]. The predictive power of the TAM model reached only 40–50% [50]. Subsequently, TAM faced a lot of criticism, which paved its way for the UTAUT framework [51].

The Unified Theory of Acceptance and Use of Technology (UTAUT) emerged as a result of combining eight frameworks [50]:

1. Technology Acceptance Model (TAM);
2. Theory of Planned Behavior (TPB);
3. A combination of TPB and TAM (C-TBP-TAM);
4. Theory of Reasoned Action (TRA);
5. Motivational Model (MM);
6. Social Cognitive Theory (SCT);
7. Model of PC Utilization (MPCU);
8. Diffusion of Innovation (DOI) Theory.

The explanatory power of UTAUT improved compared to TAM and reached 70% [52]. The first version of the UTAUT framework examined whether technology can be helpful in the workplace environment. Just under a decade later, the authors expanded the use of the model to the context of consumer products. This is how UTAUT-2 emerged [53].

The UTAUT-2 became more integrative than the rest of the previous frameworks by accumulating and building on their experience [54]. UTAUT-2 has a slightly higher explanatory power than UTAUT, predicting 74% of behavioral intention and 52% of use behavior [55]. It can serve different technologies and contexts, especially mobile phones [56], which makes it appropriate for this research.

2.3. UTAUT Framework and Recycling

Multiple studies have applied the UTAUT to evaluate mobile ICTs acceptance. Dhiman et al. [57] inspected the adoption of a fitness app by adding two constructs to the original model: self-efficacy and personal innovativeness; the former came to be the most significant predictor of use intention. Liu et al. [32] investigated the intention to use a physical activity app and found performance expectancy to be the most powerful determinant. Palau-Saumell et al. [58] tested acceptance of a restaurant app and discovered that habit was the primary driver of use intention, and technology experience had a significant moderating effect. Sharma et al. [59] extended the original framework with two constructs: information quality and trust; the latter, in addition to performance expectancy, were the strongest drivers of a government app adoption. Thusi [36] found performance expectancy and facilitating conditions to be significant predictors of the intention to use a banking app, in the context of emerging countries.

However, previous studies have only recently inspected ICTs from the perspective of socially responsible behaviors like recycling. For example, Juaneda-Ayensa et al. [40] examined the adoption of a Spanish mobile recycling app. They extended the original UTAUT-2 model by adding two exogenous constructs: impact awareness and desire for notoriety, which happened to be the main predictors of intention to use the app. They have also added an endogenous construct: intention to recycle, which turned out to be positively affected by the intention to use the app [40].

Another example of research on green ICTs is an American study about conference apps, also referred to as green information systems, which serve to decrease carbon emissions and paper waste [60]. Singh added two new variables to the original UTAUT-2 framework: ecological beliefs and attitude toward conference apps. The latter came to be the most powerful determinant of behavioral intention [60]. Given a limited number of studies in the context of green ICTs, further research is needed.

2.4. Proposed Research Model and Hypotheses

In the case of this study, waste management apps do not provide direct benefits to their users, compared to consumer apps [60]. Instead, recycling apps rely on users' voluntary initiatives to help the planet. Hence, this study will use the UTAUT-2 framework in the public service context, to understand the adoption behavior of the recycling app. To the best of our knowledge, only a small number of studies have applied this framework to the context of environmental technologies.

Another reason this study selected UTAUT-2 as a theoretical background is that the constructs and measurement scales were validated by multiple previous studies in technology adoption, thus proving the efficiency of this method. Figure 1 demonstrates the constructs used in this research. An explanation of each construct follows.

2.4.1. Performance Expectancy (PE)

Venkatesh et al. [53] (p. 159). define PE as "the degree to which using a technology will provide benefits to consumers in performing certain activities". They found that PE is one of the most powerful predictors of behavioral intention. In this study's context, if users consider the recycling app helpful in their recycling activities, such as learning what goes where, receiving reminders of curbside collection schedule, etc., they are likely to have a high intention to use the app. Constructs equivalent to PE have appeared in other models: "perceived usefulness (TAM/TAM2 and C-TAM-TPB), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT), and outcome expectations (SCT)" and became the basis for this variable, eventually [51] (p. 447). Gao et al. [61] confirmed that PE has a significant effect on the intention to use online household e-waste collection services. Hence, this study's first hypothesis is as follows:

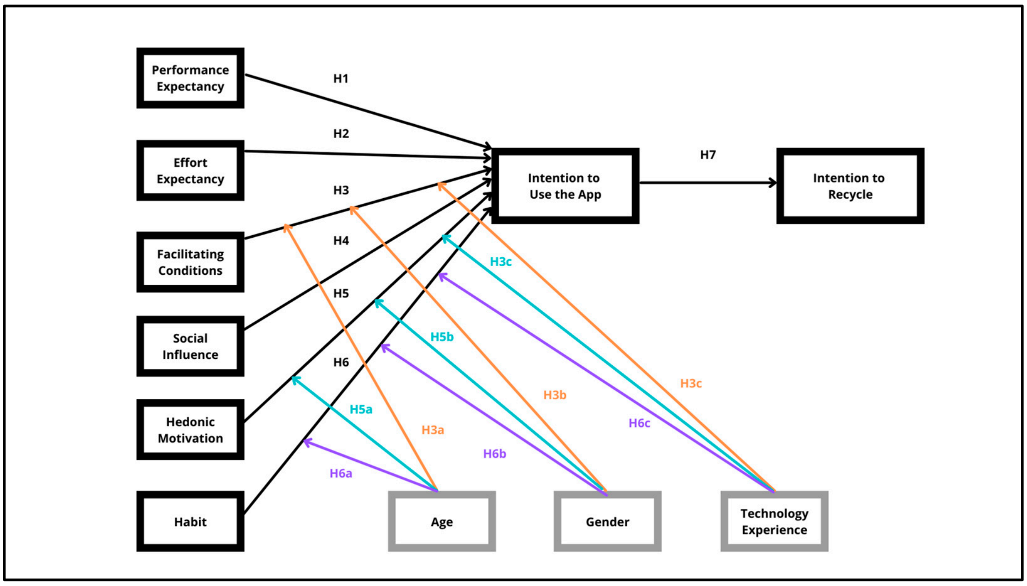

Figure 1. UTAUT-2 model that demonstrates the constructs inspected in this study. The hypotheses of the study build upon the UTAUT-2 framework, respectively.

Hypothesis 1. *The performance expectancy for the recycling app has a positive effect on the intention to use the app.*

2.4.2. Effort Expectancy (EE)

Venkatesh et al. [53] (p. 159) characterize EE as "the degree of ease associated with consumers' use of technology". According to Venkatesh, EE is likely to determine the intention to use technology. The EE concept builds on three similar variables from previous frameworks: "perceived ease of use (TAM/TAM2), complexity (MPCU), and ease of use (IDT)" [51] (p. 450). In this study's context, it means that if the recycling app is easy to use, the user is more likely to have an intention to use the app. Thompson et al. [62] found that the more familiar users are with the technology, the less significant EE becomes. Another study discovered that females consider EE more significant than males [63]. Also, older people have more salient EE than younger people [64]. Gao et al. [61] found that EE is the strongest predictor of intention to use online household e-waste services. Accordingly, this study hypothesizes that:

Hypothesis 2. *The effort expectancy for using the recycling app has a positive effect on the intention to use the app.*

2.4.3. Facilitating Conditions (FC)

According to Venkatesh et al. [53] (p. 159) FC are "consumers' perceptions of the resources and support available to perform a behavior". Venkatesh suggests that FC predicts the intention to use technology. In other words, if users have necessary resources, like a device, support services, compatible operating systems, etc., they would be willing to use the recycling app [40]. FC construct originates from the concepts inspected in previous studies: "perceived behavioral control (TPBI DTPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT)" [51] (p. 453). Juaneda-Ayensa et al. [40] discovered that FC is one of the main determinants of intention to use a recycling app. Thus, this study examines the following hypothesis:

Hypothesis 3. *The facilitating conditions have a positive effect on the intention to use the recycling app.*

Hypothesis 3a, 3b, 3c. *Age, Gender and Technology Experience will moderate the influence of FC on IU.*

2.4.4. Social Influence (SI)

Venkatesh et al. [53] (p. 159) explain SI as "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology". Venkatesh implies that SI is one of the predictors of behavioral intention. Thus, people important to the user influence their intention to use the recycling app, in this study's case. The concept of SI relates to similar constructs from previously existing models: "subjective norm (TRA, TAM2, TPB/IDTPB, and C-TAM-TPB), social factors (MPCU), and image (ID)" [51] (p. 451). Environmental psychologists discovered that the more aware individuals are of ecological issues, the higher the social pressure, which positively affects their pro-environmental behavior [65–67]. Gao et al. [61] confirmed that SI has a significant effect on users' behavior intention. Hence, this study inspects the following hypothesis:

Hypothesis 4. *Social influence has a positive effect on the intention to use the recycling app.*

2.4.5. Hedonic Motivation (HM)

According to Venkatesh et al. [53] (p. 161), HM is "the fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance". HM predicts the behavior intention to use the technology, in this case, a recycling app. If the app evokes pleasure due to its gamification elements, aesthetics, etc., the intention to use the app is likely to be high. Singh [60] found that HM was one of the key determinants of behavioral intention to adopt sustainable IS, namely, conference apps. Previous research has found that if the app triggers pleasant emotions, the users are more likely to develop desired behavioral intentions [47,48] (p. 1). It should be noted that hedonic motivation is closely connected with another UTAUT-2 construct: habit. At the initial stages of habit formation, humans require emotional rewards to associate cues and actions with pleasure [68]. For example, when people use social media on mobile phones, their brain releases dopamine, a chemical associated with satisfaction [69]. This way, a person starts associating a cue (their phone) with an action (using social media) and the reward (pleasure), and repeat this behavioral pattern until it is automatic (Wood, 2019).

As a result, this study offers the following hypothesis:

Hypothesis 5. *Hedonic motivation has a positive effect on the intention to use the recycling app.*

Hypothesis 5a, 5b, 5c. *Age, Gender and Technology Experience will moderate the influence of HM on IU.*

2.4.6. Habit (HA)

Habit has been defined as a "perceptual construct that reflects the results of prior experiences" [53,70] (p. 161). One should mind the two crucial distinctions between habit and technology experience [53].

- Technology experience is a mandatory, but not the only precondition, of forming a habit;
- Technology experience implies a span of chronological time (i.e., how long a user has been engaging with the technology); the greater the experience, the stronger the habit.

Venkatesh suggests that habit affects the intention to use the app. In this study's context, if the users find that they use the app automatically, they are likely to have a high behavior intention. Singh [60] found that habit was one of the main determinants of behavioral intention to adopt green IS, namely, conference apps.

Hence, the next hypothesis is:

Hypothesis 6. *Habit has a positive effect on the intention to use the recycling app.*

Hypothesis 6a, 6b, 6c. *Age, Gender, and Technology Experience, will moderate the influence of HA on IU.*

2.4.7. The Impact of Technology on Recycling Behavior

Juaneda-Ayensa et al. [40] speculate that previous studies have explored how old media, such as television, shapes the views on environmental issues; how news media triggers sustainable behaviors; and e-commerce promotes electronic (e-waste) recovery. However, they note that there are few studies about the effects of new ICTs, such as recycling apps, on pro-environmental behaviors. They thus hypothesize that the "intention to use a recycling-based mobile application has a positive effect on recycling intention" and confirm this hypothesis [40] (p. 9). As a result, this research also seeks to interrogate this relationship:

Hypothesis 7. *Intention to use the recycling app has a positive effect on users' intention to recycle.*

It should be noted that previous studies inspecting green app adoption using the UTAUT framework have not tested moderating variables such as gender, age, and technology experience. For example, Singh [60] argues that they focused on new constructs rather than existing relationships and moderators, but highly recommends testing moderators in future studies on green ICTs. Juaneda-Auensa [40] also drops moderators and focuses on the extensions of the model. Thus, this study is the first to test the moderating effect of age, gender, and experience, in the recycling ICTs context.

This study has removed the original construct of price value. The reason for this is that the users do not pay directly for the recycling application inspected in this study; their municipality purchases the app for them. Since price value implies a cognitive tradeoff between the cost and benefit ratio, the variable does not apply to this study. Another construct the study removed was use behavior. The decision to remove these two constructs is in line with existing research on green ICTs, using the UTAUT framework [54,60].

3. Materials and Methods

3.1. Instrument Development

A survey questionnaire was developed based on measurement scales adopted from previous studies. The questionnaire was pretested through a pilot study with five experts in the relevant field. A pilot study was conducted to test the validity and completion rate of the questionnaire. The survey questionnaire and protocol were approved by the Research Ethics Board at Ryerson University, prior to survey distribution. Table 1, below, displays the measurement scales.

3.2. Data collection

Data for this research was collected using an online survey. Uniquely to the data set, all participants were users of the same recycling mobile app technology. The research team worked with an industry partner who shared access to the survey with the New Jersey user population, where the app is provided for free to residents by their municipalities. All app users were provided with the opportunity to link to the survey using a pop-up. A convenience sampling method was used. A total of 1215 responses were received in the period of one week, surpassing the 384 responses needed for a population of this size. The descriptive statistics of the respondents are representative of the population and presented in Table 2.

Table 1. Measurement scales adopted from previous studies.

Construct (# of Items)	Name	Survey Items	Ref.
Perceived expectancy (4)	PE1	The recycling app is useful for recycling household waste.	[53]
	PE2	The recycling app saves me time in looking for information about the recycling of household waste.	[53]
	PE3	The recycling app helps me to recycle waste properly.	[53]
	PE4	The recycling app helps me understand the impact of my recycling on the environment.	[40]
Effort expectancy (3)	EE1	Learning to use the recycling app is easy.	[53]
	EE2	My interaction with the recycling app is intuitive.	[40]
	EE3	The recycling app is easy for me to use.	[53]
Facilitating conditions (4)	FC1	I have the necessary devices to use the recycling app.	[53]
	FC2	I have the necessary knowledge to use the recycling app.	[53]
	FC3	Recycle recycling app is compatible with my operation system.	[40]
	FC4	I can get help from others when I have difficulties using the recycling app.	[53]
Social influence (4)	SI1	People who are important to me think I should use the recycling app.	[53]
	SI2	People who influence my behavior think that I should use the recycling app.	[53]
	SI3	People whose opinions I value prefer that I use mobile the recycling app.	[53]
	SI4	Municipalities prefer that I use the recycling app.	[40]
Hedonic motivation (3)	HM1	Using the recycling app is fun.	[53]
	HM2	Using the recycling app is enjoyable.	[53]
	HM3	Using the recycling app is entertaining.	[53]
Habit (3)	HA1	The use of the recycling app has become a habit for me in my recycling activities.	[53]
	HA2	I am addicted to using the recycling app for my recycling activities.	[53]
	HA3	I must use the recycling app for my recycling activities.	[53]
Intention to use the app (3)	IU1	I intend to continue using the recycling app in future recycling activities.	[53]
	IU2	I will always try to use the recycling app in my daily recycling activities.	[53]
	IU3	I plan to continue to use the recycling app frequently for my recycling activities.	[53]
Intention to recycle (4)	IR1	I intend to recycle any recyclable household waste.	[40]
	IR2	I believe that in the future I will recycle household waste.	[40]
	IR3	I believe that recycling household waste will become normalized in my daily life.	[40]
	IR4	I intend to make a habit of recycling household waste.	[40]

Table 2. Descriptive information about the survey respondents.

Construct	Survey Items	Frequency	Percentile	Ref.
Age	18–24	38	3.13	[53]
	25–34	324	26.67	
	35–44	383	31.52	
	45–54	254	20.91	
	55–64	148	12.18	
	65+	68	5.60	
Gender	Man	502	41.32	[53]
	Woman	670	55.14	
	Non-binary	1	0.08	
	Prefer not to disclose	39	3.21	
	Prefer to specify	3	0.25	
Education	Less than a high school diploma	7	0.58	[60,71]
	High school diploma or GED	109	8.97	
	Some college, but no degree	190	15.64	
	Associates degree	104	8.56	
	Bachelor's degree	456	37.53	
	Master's degree	263	21.65	
	Professional degree	31	2.55	
	Doctorate	46	3.79	
	Other	9	0.74	
Household composition	Single occupancy	139	11.44	[72]
	Married/cohabiting with no dependent children	324	26.67	
	Married/cohabiting with dependent children	593	48.81	
	Single parent family	80	6.58	
	Other multi-person households (e.g., dormitory, shared residence)	57	4.69	
	Other	22	1.81	

In responses to some questions, participants could opt for "other" or "prefer to specify" and input desired information. For example, 0.25% of respondents preferred to specify their gender but did not include any intelligible information. Further, 0.74% selected "other" for education and input answers, such as "trade school, IT certificate, vocational school, automotive technician", and others. Finally, 1.81% of respondents specified other for their household composition, adding information such as "a widower with an adult child, live with an elder parent, multiple generations, extended family", and more.

3.3. Method of Analysis

Partial least squares structural equation modeling (PLS-SEM) was used to analyze the data set. SEM is a multivariate technique that allows for examining a series of relationships between a set of constructs represented by several variables (e.g., scales), and it also accounts for measurement error [73]. As SEM enables the testing of all relationships simultaneously, it is widely applied.

This technique is suitable for this study as: the UTAUT-2 model is complex and includes multiple constructs, indicators, and relationships; the sample is large; there are extensions to the original UTAUT-2 model; and the UTAUT-2 framework is tested from the predictive perspective [74]. Moreover, most previous recycling-related studies have used PLS-SEM for data analysis [40]. The software used was SmartPLS, as it was designed for PLS-SEM analysis specifically, and it has a graphical user interface that makes it convenient.

4. Results and Discussion

4.1. Sampling Adequacy

Before testing the measurement model, Kaiser-Meyer-Olkin (KMO) and Bartlett's Test helps to determine if the data is suitable for the factor analysis [75]. The test provides sampling adequacy metrics for the model. The acceptable KMO value ranges between 0.6 and 1 [75]. Table 3 shows the KMO value is 0.946; this indicates that sampling is adequate, and the study may proceed with the factor analysis. Bartlett's Test of Sphericity should be below 0.05 [76]. Table 3 demonstrates that it is 0.000, which meets the requirement, and reveals that the dataset qualifies for the data reduction technique [76].

Table 3. KMO and Bartlett's Test measures sampling adequacy.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.946**
Bartlett's Test of Sphericity	Approx. Chi-Square	32,942.140
	df	528
	Sig.	0.000

4.2. Measurement Model

One can check if constructs are valid by looking at convergent and discriminant validity [74]. Table 4 shows the results for convergent validity: each item has factor loadings over 0.70; and each construct's average variance extracted (AVE) is no less than 0.50. These are the required values to confirm the constructs' validity [77]. Item FC4 had loading values of less than 0.70, and was therefore deleted [77]. The VIF score determines how well an independent construct is explained by its items [78]. The maximum level of VIF is 5 [79]. Thus, IR, IR4, SI2, SI3, and SI4, were deleted, as their VIF value exceeded this standard.

Cronbach's α and composite reliability help assess whether the construct is reliable [80]. Table 4 demonstrates that all items have Cronbach's α and composite reliability greater than 0.70, an adequate cut-off, as per requirements [74]. Thus, all measures are adequately reliable.

Table 4. The results of the measurement model check the validity of constructs.

Construct	Items	Factor Loading	Variance Inflated Factor (VIF)	Cronbach's α	Composite Reliability	Average Variance Extracted (AVE)
Effort Expectancy	EE1	0.929	3.815	0.918	0.948	0.86
	EE2	0.908	2.692			
	EE3	0.945	4.35			
Facilitating Condition	FC1	0.945	4.353	0.936	0.959	0.886
	FC2	0.94	3.966			
	FC3	0.94	3.857			
	FC4	(loading < 0.70, the item was deleted)	(Deleted during the factor loading analysis)			
Habit	HA1	0.835	1.462	0.82	0.891	0.732
	HA2	0.857	2.443			
	HA3	0.875	2.493			
Hedonic Motivation	HM1	0.955	4.988	0.923	0.951	0.866
	HM2	0.938	3.978			
	HM3	0.898	2.825			
Intention to Recycle	IR1	0.891	2.946	0.944	0.96	0.857
	IR2	0.939	4.816			
	IR3	0.934	(VIF value > 5, the item was deleted)			
	IR4	0.938	(VIF value > 5, the item was deleted)			
Intention to Use the App	IU1	0.876	2.233	0.867	0.919	0.791
	IU2	0.859	2.187			
	IU3	0.931	3.227			
Performance Expectancy	PE1	0.876	2.979	0.895	0.927	0.762
	PE2	0.897	3.2			
	PE3	0.917	3.398			
	PE4	0.797	1.928			
Social Influence	SI1	0.911	3.974	0.912	0.939	0.795
	SI2	0.926	(VIF value > 5, the item was deleted)			
	SI3	0.935	(VIF value > 5, the item was deleted)			
	SI4	0.785	(VIF value > 5, the item was deleted)			

Discriminant validity constitutes the fact that a construct has a stronger relationship with its own indicators than those associated with any other construct in the path model [81]. It is recommended to use the HTMT criterion to assess discriminant validity [79]. An acceptable HTMT value for establishing discriminant validity between two constructs is one below 0.90 [79]. Table 5 shows that all constructs satisfy this criterion for discriminant validity.

Table 5. Heterotrait-Monotrait Ratio (HTMT) results.

Variables	EE	FC	HA	HM	IR	IU	PE	SI
EE								
FC	0.729							
HA	0.547	0.341						
HM	0.553	0.324	0.805					
IR	0.5	0.597	0.401	0.362				
IU	0.662	0.566	0.845	0.676	0.643			
PE	0.857	0.728	0.62	0.561	0.526	0.74		
SI	0.488	0.309	0.703	0.658	0.359	0.575	0.52	

4.3. Structural Model

Analyzing the structural model helps determine the predictive power of the framework and test the hypotheses of the study. As seen in Table 6, R2 values are 0.347 for intention to recycle and 0.651 for intention to use the app. This means that the independent variables account for 34.7% and 65.1% of the variance in the dependent variables, respectively (i.e., intention to recycle, intention to use the app).

Table 6. R-Square results reveal the model's predictive power.

Variables	R^2
Intention to recycle	0.347
Intention to use the app	0.651

The next step is to test the hypotheses by doing the path analysis. As shown in Table 7 and Figure 2, each path represents a hypothesis. The higher the path coefficient value (β), the stronger the relationship between dependent and independent variables [82]. All the β values are significant at $p < 0.05$ [83].

Table 7. Path analysis results: each path represents a hypothesis.

Hypothesis	Path	Path Coefficient (β)	t-Value	Standard Deviation	*p*-Value	Comment
H1	PE $\geq$ IU	0.189	4.43	0.043	0	Supported
H2	EE $\geq$ IU	0.049	1.323	0.037	0.186	Not supported
H3	FC $\geq$ IU	0.195	4.885	0.04	0	Supported
H4	SI $\geq$ IU	0.042	1.626	0.026	0.104	Not supported
H5	HM $\geq$ IU	0.086	2.79	0.031	0.005	Supported
H6	HA $\geq$ IU	0.454	14.596	0.031	0	Supported
H7	IU $\geq$ IR	0.589	15.05	0.039	0	Supported

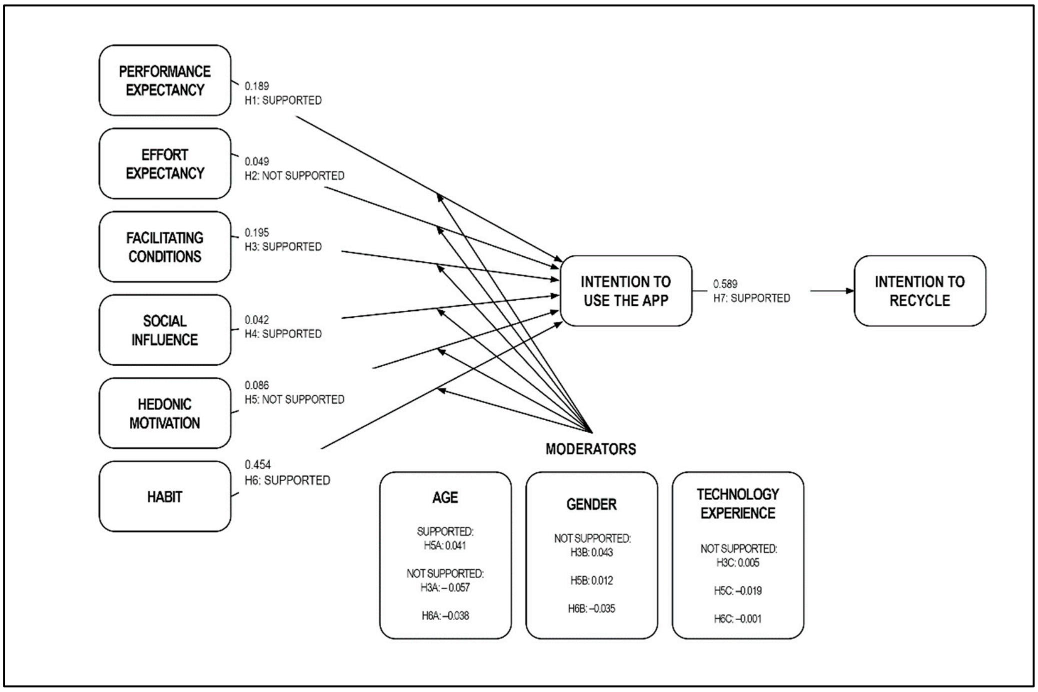

Figure 2. Path analysis results that demonstrate path coefficients (β).

4.4. Path Analysis

4.4.1. Supported Hypotheses

Five hypotheses were supported by the path analysis results. Findings reveal that PE is a significant predictor of IU; this is consistent with previous green technology research [61,84]. However, another study on green ICTs found no salient link between PE and IU; they assume it could be because environmental technologies, such as conference apps, do not affect users' performance in conferences or jobs [60]. Conference apps aim to substitute the use of paper and help attendees proceed through their conference experience while caring for the environment [60]. In the case of this study, it is different; recycling is not a one-time occurrence, as opposed to the conference. Therefore, it is reasonable for users to expect that the app will help them in their recycling activities. This study offers an implication for recycling app developers; if they want their users to be willing to use the app, they should make it helpful for recycling activities (provide high-quality recycling education articles, videos, quizzes, etc.).

FC has a significant relationship with IU, which is in line with Juaneda-Ayensa et al. [40]. Previous research on ICTs and digital marketing confirms that having the necessary means to use technology positively affects usage intentions and behaviors [85–89]. Therefore, recycling app providers should ensure their users have a suitable device with sufficient capacity to access the app, and have basic knowledge of using the device. Providing customer service to create a user-friendly environment is important, making use of the app more likely. It is possible to offer small workshops (online if necessary) to train users on using the app, or create an automatic in-app tutorial for new users.

HM is a significant predictor of IU; this is in line with previous research [60]. Previous scholars revealed that hedonic motivation emerges when the users obtain new information from technology [90]. Thus, because the recycling app inspected in this study educates residents on recycling, it contributes to users' hedonic motivation and makes them continuously want to use the app. Hedonic motivation may differ depending on the app features, e.g., play, quantification, interaction with other users, etc. [60]. One idea for increasing hedonic motivation for recycling apps is to use the quantification technique [91]. If users see how much positive impact they made on the environment, via progress bars or other data visualization methods, they become more likely to use the app. Previous studies empirically supported this claim [40,42]. Thus, developers may want to evaluate and choose the most efficient ways to facilitate hedonic motivation.

Also, HA has a significant relationship with IU. To the best of our knowledge, no previous studies on green technology adoption tested this linkage. Scholars have previously found habit to be a significant driver in technology adoption [70,92,93]. Researchers have looked at habit as an outcome of both a belief system and providing the necessary infrastructure to make behaviors automatic [69,94]. Hence, the developers of the recycling app can promote the app to new users to instill a positive belief about the app, and subsequently trigger habitual use. Also, they can set the context in a way which will lead to repetitive use and ultimate automaticity: i.e., deliver pop-up notifications prompting to enter the app; make the app icon salient and bright; and conduct usability testing to enhance user experience. Fostering the habitual use of the app would naturally foster an intention to use the app. Keeping in mind the structure of habit formation, stimulus–action–reward [69], app developers can facilitate a pleasant and engaging user experience by using gamification techniques. This way, users will associate the app with pleasure and return for emotional rewards regularly, which will create a sustainable habit.

Finally, the results demonstrated a significant relationship between IU and IR. This is in line with Juaneda-Ayensa et al. [40]. This result offers implications that municipalities should consider recycling apps in addressing the recycling education problem, as there is empirical evidence that recycling apps foster the intention to recycle waste. The technology interrogated in this research represents an example of ICT investment at the municipal level. Understanding if it has a positive impact on municipal recycling programs is, thus, helpful in shaping these programs to improve overall outcomes.

However, effects may vary depending on individual recycling apps. The results obtained in this study can potentially extend to other sustainability-focused behaviors, such as consumption reduction, and participating in circular reuse/return systems, etc. Understanding how to improve the update of mobile applications can be a fruitful investment for sustainability-focused education.

4.4.2. Rejected Hypotheses

Two hypotheses were not supported by the path analysis. The linkage between EE and IU was not significant, which contradicts the findings of previous studies on sustainable technology adoption [60,61,84]. This outcome could have occurred because most respondents (over 60%) have used the app for more than one year, and thus do not have difficulty in using the technology. Also, most users fall under the age category of 25–44; this could mean they face little difficulty using technology. As of 2020, smartphone adoption among Americans aged 50+ was 77%, but even though older people are becoming more tech-savvy, younger adults use smartphones more frequently and for more diverse purposes [95]. Hence, expectations about ease of use do not affect respondents' intention to use the recycling app.

The relationship between SI and IU is also not significant. This finding is consistent with other green technology studies [40,60]. Juaneda-Ayensa et al. [40] suggest that the failure to find a relationship between SI and IU could be because using a recycling app is a personal activity. It is possible that as recycling applications become more commonplace, social influence will play a greater role. Further, integrating social components into the apps can increase this relationship. In the case of this study, municipalities provide the recycling app, and thus residents do not feel social pressure to establish the intention to use the app. Instead, they do it by default; they pay taxes and thus expect municipalities to provide high-quality community recycling programs. This is not associated with social norms but rather with the expectations of public service providers. Some IS, such as social networks, provide access to the community of the users, where people can interact, express themselves, and receive social acknowledgement [96]. It is not the case for a recycling app inspected in this study, as it does not facilitate communication between the users. However, research on an online e-waste collection service in China found that social influence is significantly related to the use intention [61]. Authors speculate that it might be because of the Chinese cultural context. Also, Gao et al. [61] mention that men were more prone to social influence than women, and recommended hiring social media influencers to spread word of mouth about the service. Recycling app developers could try launching a group on social media and inviting the users to create a sense of belonging to the group of sustainability-minded people.

4.5. Moderators

As seen in Table 7 and Figure 2, the only case with a statistically significant moderating effect is age moderating the path hedonic motivation $\geq$ intention to see the app ($\beta = 0.058$, $p < 0.05$). Hedonic motivation has been shown as being tied to age in other studies [97]. In ICT research, there remains a lack of consensus on whether age is a critical moderating variable [98]. In this study, the age moderator strengthens the path relationship between HA $\geq$ IU. The effect size of this interaction is calculated at 0.029, indicating a weak effect [99].

All of the other moderators are not significant in this model. It is possible that recycling, and by extension a recycling app, is seen as fairly ubiquitous, thus, no interaction effect from gender and age (in most cases) is present. Likewise, given the simple nature of the app being tested, technology experience is not significant in strengthening (or weakening) the intention to use the app. As mentioned in the theoretical background section, other studies on green ICTs have dropped moderating variables [40,60].

4.6. Limitations and Future Research

One limitation of this study is that the sample is comprised of New Jersey residents, and may not fully represent the entire population of other U.S. states. Another constraint is that the results may not be generalizable to all mobile recycling applications, as their features might differ.

The findings apply to the users of the particular application, which could provoke survivorship bias. It implies focusing on the users of an existing app, while overlooking the input of those who quit, or have never used the app. This study aimed to inspect what factors positively affect the intention to continue using the existing app, rather than predicting the usage of a new app, so the input from non-users was out of scope in this case; however, it is highly encouraged in future research. Another limitation could be the social desirability bias; users could respond to the sustainability-related questions in a favorable fashion. Future studies could incorporate ethnographic research methods, such as observation and customer journey mapping, to compare actual behavior with the survey responses [100].

As for the further direction of this study, the funding mechanisms of the recycling application, such as corporate sponsorship, will be inspected. Sustaining and developing a pro-social app, let alone acquiring new users, requires financial investments. From the perspective of the municipalities, resources allocated for recycling education are limited as running waste management programs entails many expenses and requires extensive funding [101–103]. This study could further examine partnerships within an app environment where specific brands' recycling, or take-back procedures, can exist. Mobile apps could become a resource for B2B recycling, reclaiming packaging, receiving credit for extended producer responsibility, and so on. Another promising direction of this research is further inspecting motivating factors for recycling, e.g., testing various gamification elements, like collecting points and dispensing coupons, to encourage learning and recycling behavior.

Future research into recycling applications adoption could include a broader geographical scope, as recycling standards and programs differ according to location. Also, other researchers could examine whether recycling apps affect actual recycling behavior and decrease recycling contamination. Finally, the efficiency of recycling apps versus traditional media, in terms of teaching residents to sort waste correctly, could also be an interesting area for further analysis.

5. Conclusions

Recycling apps are an innovative approach to much-needed environmental education, and thus there is a need to study the adoption of such ICTs. This study applied the UTAUT-2 framework to examine the determinants of intention to use the recycling app and recycle household solid waste, focusing on the New Jersey context. Findings suggest that performance expectancy (PE), facilitating conditions (FC), social influence (SI), hedonic motivation (HM), and habit (HA), have a positive effect on the intention to use the recycling app (IU). However, effort expectancy (EE) and social influence (SI) were not statistically significant, and thus their impact on intention to use the app (IU) was not supported. Of all moderators, only age demonstrates a significant effect on one path: HM $\geq$ IU. It is promising to see that intention to use the app (IU) had a positive impact on the intention to recycle (IR). This indicates that ICT technology can be used to improve consumer-facing sustainability outcomes.

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