Article

The Potential Determinants for Smartphone Recycling Behaviour Sustainability in UAE

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Abstract: Repeated actions and behaviours are characteristic of people's daily lives. However, there is a dilemma when this repeated action is associated with mobile phone recycling since convincing mobile users to recycle sustainably is challenging. This study analysed the four factors (i.e., actual knowledge, salience, environmental constraints, and habits) adopted from the Integrated Behavioural Model (IBM) theory and examined their impact on behavioural sustainability. A partial least squares structural equation modelling (PLS-SEM) approach was applied to evaluate 601 responses from a self-administered online survey collected from mobile user participants based in the United Arab Emirates (UAE). The survey findings indicated that habit has the strongest and statistically significant positive influence on behaviour; followed by knowledge and skills. Additionally, the salience of behaviour has a considerably negative influence on behaviour sustainability unaffected by environmental constraints. This study serves as a springboard for future research examining the IBM model to understand recycling behaviour in general and smartphone recycling sustainability in particular. Additionally, this research can assist smartphone manufacturers in understanding the factors that will maintain the recycling behaviour continuity, increasing the number of returned devices.

Keywords: mobile phone recycling; smartphone recycling; customer recycling behaviour; Integrated Behavioural Model; recycling sustainability

1. Introduction

Numerous businesses and organisations are currently implementing various strategies for collecting end-of-life (EOL) and end-of-use (EOU) smartphone or mobile phone devices to generate extra profit by selling excellent condition devices in a second market, reusing some parts for new manufacturing, or claiming to be environmentally friendly. Moreover, a massive amount of electronic waste (e-waste) is generated from discarded smartphone devices. Therefore, many studies focused on studying the factors that influence customers to participate in recycling processes [1]. Around 50 million tonnes of electronic and electrical garbage (e-waste) are generated each year, the equivalent of all the commercial airplanes ever constructed, and barely 20% of this waste gets recycled properly [2]. If nothing is done, e-waste will more than treble, reaching 120 million tonnes by 2050 [3]. Similarly, e-waste poses a massive potential material value of $US 62.5 billion, three times the yearly production of the world's silver mines and more than the gross domestic product of most nations. Recycling one million mobile phones generates and conserves 24 kg of gold, 9000 kg of copper, 250 kg of silver, and 9 kg of palladium [4]. Additionally, collecting minerals from discarded devices generates far less carbon dioxide than mining in the earth's crust [3].

The cadmium contained in a mobile phone battery is sufficient to contaminate 600,000 L of water. Additionally, illegal incineration can result in the release of toxic gases into the

air, posing a serious health risk to both humans and animals [4]. However, the electronic items and components that function correctly are worth more than the resources they contain. Therefore, increasing the useful life of goods and reusing components result in an even more significant economic gain [4]. The popularity of smartphones over other electronic devices is due to their high consumption volume and the fact that each year numerous companies compete to announce new smartphone devices with new features and styles. Besides, such devices have a short life cycle, typically two to three years [5,6]. The number of mobile phone users will increase from about 6.95 billion in the year 2020 to about 7.49 billion in the year 2025 worldwide [7]. The United Arab Emirates (UAE) has mobile subscriptions of up to 209 for every 100 people [8]. In light of this, the current study's survey is conducted in the UAE, covering all seven cities or emirates. The UAE has lately increased the focus on the rising problem of e-waste by creating the world's biggest e-waste recycling facility in the Dubai Industrial Park [9]. While existing literature has also been limited to examining the e-waste recycling sustainability behaviour, most studies examine the e-waste recycling behaviour [10–13], not focusing on behaviour continuity. Also, existing studies focus on evaluating the risk and developing decision tools for achieving sustainability in e-waste recycling [14] or on e-waste collection strategies to promote a culture toward sustainability [15]. This study unlocks this gap by examining the factors that will contribute to the long-term sustainability of behaviour.

The Theory of Planned Behaviour (TPB) model, which can be considered an old theory, was proposed in 1985 by Icek Ajzen [16]. The model requires an association with new behavioural models to examine behaviour continuity. However, the TPB theory itself is one of the most robust theories, which allows for the examination of behaviour despite the exclusion of factors determining behaviour continuity in the model. With the focus on mobile devices' short life cycle, there is a need to study the factors that affect smartphone recycling behaviour continuity. According to the resources available to the authors, no model was found to be examining this point. Therefore, this paper seeks to adopt factors from the Integrated Behaviour Model (IBM). The IBM theory is a combination of the Theory of Reasoned Action (TRA) and TPB, and is considered to be an extended version of the two theories combined, which was developed by Fishbein [17]. IBM verifies that intention is the main factor in predicting behaviour. However, the IBM introduces new determinants that can help change the intention to perform a behaviour [16,18]. IBM factors comprise attitude, perceived norms, and personal agency (which will not be examined and evaluated in this paper). The IBM posits four additional factors that may propel the behaviour sustainability, those factors are: knowledge and skills, salience of recycling behaviour, environmental constraints, and habits. These factors—which will be examined by this paper- affect the behaviour directly, as this model has been applied in the medical and health sectors to analyse the consistency of patients' behaviour when it comes to taking medication. The knowledge and skills to perform the behaviour of smartphone recycling can be defined as the knowledge about mobile device waste and ways to identify the actions required for recycling mobile devices [19]. For salience of behaviour, if an individual intends to perform a behaviour (mobile phone recycling/reuse) but is unaware of the importance of such behaviour, it is likely they will not perform this behaviour [20]. Environmental constraints or restrictions refer to the external or socio-environmental challenges that might block or restrict individuals from performing a behaviour [17]. Finally, habit is defined as a repeated past behaviour; for mobile phone recycling or reuse behaviour, it should be associated with the individual's memory as a repeated experience [19]. There is a shortage of attention on examining the factors associated with IBM and determining if they contribute to behaviour continuity. Therefore, this study aims to address this gap by conducting an empirical survey to measure the four factors that are proposed by the IBM theory (actual knowledge, salience, environmental constraints, and habits) and to determine whether those factors will have a role to enhance behaviour sustainability. It is essential to highlight that mobile phones are devices used to make calls, send messages, and are characterised by a physical keyboard. Whereas smartphones have a virtual touchscreen, used like personal assistants

to reply to emails, monitor our health, find our location on maps, watch videos, and buy products on the internet [21]. However, this study will not focus on this differentiation as the main focus is to study the recycling behaviour continuity.

2. Literature Review

2.1. Sustainability of the Behaviour

Examining and identifying the components that lead to regular recycling behaviour is critical for behavioural sustainability. The study by Sardar Donighi and Yousefi [22] highlighted that service quality and post-purchase value greatly affected the level of customer satisfaction. The results found that post-purchase intention and behaviour would differ based on the service quality provided and the perceived value. A study by Kuo et al. [23] of mobile users reported similar findings; service quality directly influenced customer satisfaction, and perceived value positively affected customer satisfaction as characterised in post-purchase behaviour. Nevertheless, these studies have led to yet another question: how to ensure customer satisfaction and behaviour continuity through mobile device recycling or providing high-quality service? According to Min et al. [24], enjoyment and payment characteristics are essential factors driving a momentous post-purchase intention. Providing easy access and an enjoyable experience throughout the reverse supply chain cycle (RSC) for mobile consumers recycling EOL or EOU mobiles encourages them to repeat the experience. Notably, assurance on data-cleaning procedures via high-quality service as part of the experience will lead to high-level consumer satisfaction. In spite of this, service quality and enjoyable experience are difficult to accomplish during refurbishing or recycling, shifting the focus to other more practical variables.

According to Corsini et al. [25], most of the research discussing the customer's circular behaviours in purchasing EOL electronic products is determined by specific practices linked to the customers' behaviours such as online recycling. Also, this study highlighted that most of the theoretical models adopted by reviewed studies were useful to predict the circular consumer's EOL electronic products purchasing behaviour. Furthermore, those studies highlighted that additional variables are required to explain the behaviour.

Bovea, Ibanez-Fores, Perez-Belis and Juan [11] Showed that e-waste management rules and economic variables drive consumer participation in the 3Rs (Repair, Reuse, and Recycle) of EOL/EOU electronic devices, which benefits the environment and natural resources. The study found that consumers, especially those who purchase small electronic devices, are still unprepared to embrace such habits. According to the results, there is a preference for retaining such devices over recycling them. Repairing is a viable alternative to recycling when the repair cost is weighed against the cost of a newly manufactured product. Also, the study highlighted that the consumers' level of education and age affect their choice to repair an old device; on the other hand, family wealth has no such effect on consumer behaviour. The study did not associate the findings with particular behavioural theory, and the factors presented were not thoroughly explored. However, the study investigated the socioeconomic factors and their effect on consumer behaviour.

Yla-Mella et al. [26] examined consumers' awareness and perception regarding mobile phone recycling or reuse in Oulu, Finland, by combining the TPB and value-belief-norm (VBN) theories. The findings indicate that consumer awareness of the importance of e-waste recycling was high among the respondents; The difficulty, however, was how this awareness might be turned into recycling behaviour. This study found that 55% of respondents had a minimum of two unused mobile phones stored at home. The main reason for this storage is the lack of recycling channels. The study concluded that this lack of behaviour is due to the recovery system which does not educate or promote the return of small e-waste. The study highlighted that more information and awareness on mobile phone recycling is vital to encourage the customers to recycle more and change their storying habits. Although such awareness is necessary, this research did not examine whether increased knowledge and promotion may contribute to the sustainability of recycling behaviours. However, this study will address this through the knowledge and skills factor.

2.2. Integrated Behavioural Model (IBM)

IBM was originally developed to help the medical sector predict health behaviours and suggest preventive action, particularly concerning human immunodeficiency virus (HIV) [27,28]. In a study conducted by Pember [27] to understand eating behaviours, IBM was used to evaluate graduate students' attitudes, subjective norms, and control beliefs, in addition to studying the knowledge, skills, and environmental factors influencing the power to change eating behaviours. To communicate a strong message of eating healthy to the students, the study found that the environmental factor, as well as knowledge and skills in the area, were the barriers to achieving healthy eating behaviour.

The IBM theoretical framework, attitudes, perceived norms, and personal agency all contribute to behavioural intention, which results in behavioural improvement or change. Although social scientists believe that behavioural intention is the best predictor of behaviours, other variables can sometimes mitigate the behaviour's continuity. As illustrated in the literature, actual knowledge of behaviour, salience, a diverse set of environmental constraints, and habits all have significant and direct effects on actual behaviour [29]. Therefore, certain behaviour is more likely to occur and be repeated if: (1) an individual has a deep desire to execute it along with the necessary expertise and abilities; (2) there are no significant environmental constraints restricting success; (3) the behaviour is salient; and (4) the person has previously practised the behaviour. These elements and their experiences must be considered when developing interventions to increase mobile phone recycling behaviour [17]. In this way, IBM will supplement other hypotheses of change, consequently improving the practice of behavioural continuity.

2.3. Knowledge and Skills

Kianpour, Jusoh, Mardani, Streimikiene, Cavallaro, Nor and Zavadskas [12] demonstrated RSC as a suitable channel for companies and individuals to use in returning or recycling EOL electronic products. The findings proved that consumer environmental knowledge coupled with associated advantages were new factors that could be added to TPB, which could influence consumer attitudes towards returning EOL products via authorised channels for reusing, repairing, and recycling purposes. Furthermore, the study verified the influence of the two factors, namely attitude and perceived behavioural control on consumer intention to participate in RSC. Despite highlighting the factors influencing consumers to reuse or recycle electronic products through RSC channels, the study did not prove that these factors promote habitual or continuous recycling behaviour, particularly for small EOL products such as mobile devices. In another study, Rosenthal [30] argued that knowledge and awareness factors diminished the connection between behaviour and intention. The author linked procedural information seeking and behaviour, assuming that the attitude towards recycling might change based on consumer knowledge.

In a recent study by Nguyen et al. [31] on understanding the willingness of individuals to pay for e-waste recycling, it was found that end-users with a higher education employed their knowledge to reduce e-waste and contribute to recycling opportunities for the betterment of the environment. Moreover, these users would even pay for e-waste recycling. The study concluded that knowledge could play a crucial factor in enhancing the level of environmental awareness and recycling behaviour. Nevertheless, the research did not indicate whether this factor contributed to the durability of the practice. When a person might intend to perform a behaviour, it is essential to have the skills and knowledge with which to perform this behaviour. Repeating the behaviour is most likely to happen if a person has the knowledge and skills required, and therefore, the below hypothesis is suggested:

Hypothesis 1 (H1). *Smartphone users' knowledge and skills positively contribute to continuous smartphone recycling behaviour.*

2.4. Salience of Behaviour

A study conducted by Taylor et al. [32] attempted to determine which main IBM factor was able to predict nurses' intentions to provide pain relief medicines that were taken "as needed" (commonly known as PRN) to hospitalised postoperative orthopaedic patients. The research showed that IBM structures were beneficial in predicting intentions towards performing a professional's behaviour. The salience of behaviour as a factor was the only significant predictor variable for the nurses' intentions to determine the provision of PRN medicine to the patients. This study may indicate that understanding the salience of a behaviour might help mobile users who participated in recycling positively tune their behaviour towards other types of recycling if needed.

Winterich, Nenkov and Gonzales [20] discussed the differing results from their research concerning why product transformation salience led to increased recycling. The primary research question raised was whether messages related to marketing recycling affected people's willingness to recycle. The research featured two distinct product transformation manufacturing conditions: one in which the transformed product was the same as the recycled product, and one in which the transformed product was different from the recycled product (i.e., a plastic bottle was transformed into a new jacket). The findings indicated that transformation salience was not based on the particular product in the transformation message. A second study by the same researcher examined whether the salience of product transformation increased recycling behaviour through advertisements by proposing a new product (phone case) made from recycled plastic. The findings supported the role of transformation salience in increasing recycling behaviour. Items marketed as having been manufactured from recycled plastic seemed to affect peoples' recycling intention. Therefore, the question required to examine is whether recycling behaviour positively increases with the salience of behaviour. Furthermore, if advertisements indicated the salience of behaviour, would they lead to continuous recycling behaviour?

The behaviour should be personally essential and salient. If a behaviour is considered necessary to an individual, the person will most likely perform a particular behaviour frequently. Therefore, the following hypothesis is proposed:

Hypothesis 2 (H2). *The salience of recycling behaviour is positively associated with continuous smartphone recycling behaviour.*

2.5. Environmental Constraints

Environmental constraints refer to the external or socio-environmental challenges that might block or limit the behaviour, even if the behaviour is derived from a firm intention. Swarna Nantha et al. [33] developed a framework based on TPB and IBM to quantify the factors related to the behaviour of Type 2 diabetes patients concerning adhering to medication. The authors regarded environmental constraints as preventing patients from following a medication regime. They also referred to environmental factors as barriers in performing medication compliance. In conclusion, the environmental constraints and other factors in TPB and IBM might prevent proper implementation of a self-regulated diabetic procedure by patients.

Studies conducted in the health sector, for example, those done by [17,19], found that to ensure changes in patients' behaviours, it was essential to ensure there were no severe environmental constraints faced by the patients. These included transportation and limited clinic hours, particularly for patients who wished to do a mammogram. The same would apply to the smartphone industry if customers intended to participate in mobile phone recycling or refurbishing. It would then be vital for the government to facilitate the process. Measures to be taken include reducing environmental constraints, such as building the right facilities or locations for mobile phone users to hand over their EOL or EOU mobiles. These facilities are to be made available in different locations individuals usually have access to, such as malls or designated spaces at bus or train stations.

Ultimately, constraints are circumstances, either human or environmental, that prevent or discourage individuals from performing an activity or improving skills. For this reason, Siddique et al. [34] emphasised that environmental constraints are a vital factor that should be eliminated or minimised to achieve continuously performing a behaviour. [34] confirmed that environmental constraints negatively influenced behaviour sustainability. Accordingly, the following hypothesis is proposed:

Hypothesis 3 (H3). *Removing any environmental constraints will positively contribute to continuous smartphone recycling behaviour.*

2.6. Habit

In the domain of mobile phone recycling, Welfens et al. [35] analysed the barriers to returning mobile phones for recycling. The study proposed that internal and external factors were vital in changing consumer behaviour, one of which, as highlighted, was habit. [35] argued that if recycling, such as that of paper or glass, were part of an individual's daily routine, the habit would be a driver of any new habit such as mobile phone recycling. On the contrary, if recycling were not part of an individual's routine, establishing a new habit would be an obstruction in this context. This obstacle would become robust if keeping old mobile devices became a habit. Interestingly, the study found that changing an individual's habit with respect to mobile phone recycling has thus far failed in current operations.

Rahman and Noor [19] proposed that habit was one of the critical factors influencing purchase behaviour. This factor was also considered an essential determinant for repeating the intention to purchase. Conventionally, habit is defined by scholars as the automatic behavioural reaction caused by situational stimuli [19,36]. A habit usually occurs due to an experience or past behaviour. Therefore, if the government or other organisations succeeded in activating a habit among consumers to participate in RSC activities for mobile phone recycling or refurbishing, they would learn future recycling behaviours. People with established habits will require less information about a specific activity, as they understand the behaviour entirely and do not need as much time to plan or prepare [30]. From a different view, as highlighted by Welfens, Nordmann and Seibt [35], habit could be considered the main behaviour driver, if the recycling of daily life materials, such as paper or glass, was already part of an individual's regular practices. If this were not the case, it would be essential to then develop an entirely new habit, which would involve a shift in the individuals' routines; else, this factor would be a barrier. In this context, it would imply that the habit of storing old mobile phones was to use them if the current phone was missing, stolen, or not functioning. Habit, in this case, would work as a barrier to recycling behaviour. This argument was crucial when designing this study's questions, as the recycling habit should be linked with previous experiences in mobile 3Rs.

A recent study by Aboelmaged [10] investigated the factors that influenced young customers' intention to recycle e-waste in the UAE. It was found that recycling habits and perceived attitudes were significant determinants of young adults' intention to recycle e-waste. The study added habit as a factor to TPB and examined the effect on intention. On the contrary, the present study attempts to observe the effect directly on the behaviour. If a person had experienced a behaviour previously, it would be very likely for the behaviour to turn into habitual behaviour. Therefore, the following hypothesis is formed:

Hypothesis 4 (H4). *Mobile phone users' recycling habit positively contributes to continuous smartphone recycling behaviour.*

Figure 1 illustrates the study's framework and the relationship of variables in terms of hypotheses.
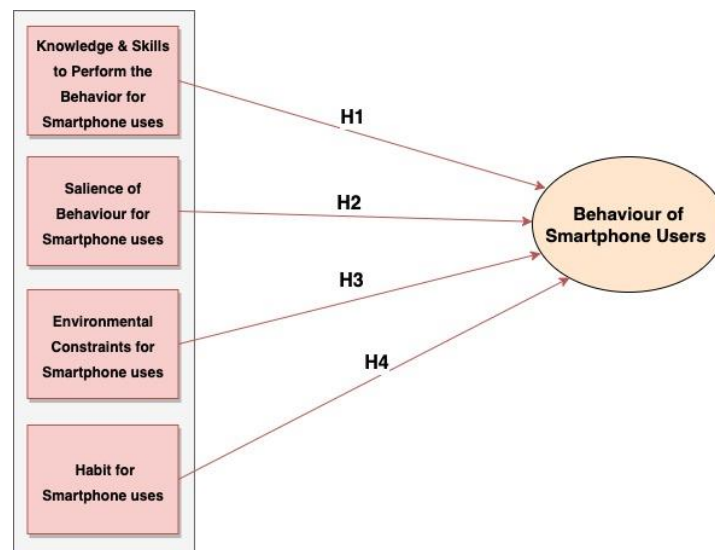
Figure 1. The conceptual framework model.

3. Research Methodology

3.1. Survey Questionnaire Design

The measurement items were examined and reviewed through multiple research and studies [6,12,30,37–43]. Questions were adapted from these studies to create the initial instrument. Table 1 presents the list of research reviewed. A panel of two supply chain management (SCM) academics and three SCM industry specialists assessed the questionnaire. The expert panel provided their suggestions and enhancements to the questionnaire. Moreover, a pilot test was conducted with 30 participants who reviewed the questions and provided their opinions and comments. The questionnaire included a closed-ended question answered on a five-point Likert scale ranging from 'Strongly disagree' (1) to 'Strongly agree' (5). And for the last five questions related to behaviour measurements, the criteria ranged from 'Never' (1) to 'Always' (5) (see Appendix A Table A1). A five-point Likert scale was employed in this research, which gave respondents satisfactory alternatives and facilitated the analysis.

Table 1. List of studies used for the survey questionnaire.

Construct	Source	No. of Items
Mobile users' knowledge and skills to perform the behaviour (MU_KSP)	[12,37,38]	4
Mobile users' salience of behaviour (MU_SB)	[12,37,38]	4
Mobile users' environmental constraints (MU_EC)	[6,39]	4
Mobile users' habit (MU_H)	[30,40,41]	4
Behaviour of mobile users (BMU)	[30,39,42,43]	5
General information and questions related to mobile phone treatment options.		
General information about the users (gender, age, education, income, and city).		

Table 1 also illustrates the number of questions assigned to each proposed factor. The survey was constructed in four parts:

1. Survey keywords and consent message.
2. Questions related to the conceptual framework variables.
3. Questions related to mobile phone recycling treatment options and respondents' opinions.
4. Respondents' demographic information.

3.2. Data Collection

The Cochran (1977) formula is used to calculate sampling size [44] by estimating the population's characteristics at 95 percent certainty with a 4 percent plus or minus margin of error, resulting in 601 questionnaires required for the UAE population = 9.89 Million [8]. A self-administered questionnaire survey was sent to the targeted respondents to obtain over 601 completed responses. Furthermore, this sample size satisfies the ten times rule [45,46], which states that the sample size should be equal to ten times the number of independent variables in the most complicated PLS mode. Self-selection data collection enables coverage of a population with a high sample size, which is good for generalising the outcome. Additionally, this strategy was both time and cost-effective since the questionnaire was sent to mobile users in seven cities around the UAE, with Abu Dhabi and Dubai accounting for 70% of the population. The respondents included locals and foreign men and women residents of the UAE.

It was difficult to send the survey to the whole population in the different UAE emirates using only the snowball strategy. Therefore, the questionnaire was distributed using the "Surview.ae" platform. "Surview" is an online service for survey creation. It is one of the most known and reliable online survey platforms in the UAE, specializing in sending survey questions to relevant respondents and collecting responses. The survey was shared by "Surview" in different time frames to target different users with various attitudes (different hours, weekdays, and weekends), to decrease bias and increase the validity of collected data. The survey was conducted from October to December 2021. The survey gathered 1983 total and incomplete replies; incomplete responses occurred because some respondents did not finish the survey; the survey concluded after accumulating 630 respondents.

3.3. Data Analysis Method

After collecting data and gathering information from the questions answered by the respondents, a screening task was required to ensure data validity and eliminate missing values [46]. Only valid data were processed to obtain accuracy prior to data analysis. The data analysis used a three-step analysis: firstly, the initial data and the demographic responses were collected and analysed using SPSS v28.0, and different statistical tests were used to analyse the collected data. Secondly, partial least squares structural equation modelling (PLS-SEM) was used as the primary data analysis technique, while the measurement analysis (outer model) was conducted first to check the convergent and discriminant validity using the SmartPLS 3.3.5 software. Finally, the structural analysis (inner model) was conducted to test the hypotheses and measure the model's explanatory power.

4. Data Analysis and Results

The collected data were declared accurate. No missing data were identified since the survey questions had been completed, and no rows from the final sample of 630 responses needed to be deleted. According to Hair Jr, Hult, Ringle and Sarstedt [46], straight-lining, however, occurs when a respondent marks the same answer for all questions. As a result, 29 replies were excluded since respondents provided the same responses to all sections, indicating that those respondents did not complete the survey honestly. Therefore, 601 final replies were retained, as this was the study's objective sample size. This study used the full collinearity test to test the common method bias (CMB) as suggested by [47]. According to [48], this is the correct method for calculating CMB as the Harman one-factor test is no longer acceptable. The full collinearity test using SPSS a regression method against a common variable showed that the variance inflation factor (VIF) for the factors: (MU_KSP = 2.622), (MU_SB = 2.412), (MU_EC = 1.326), (MU_H = 2.465) and (BMU = 1.230). As the VIF is less than 5, indicating that single source bias is not a significant problem with our data.

4.1. Descriptive Statistics of the Respondents

The respondents' general background was assessed first, which included their gender, age, educational level, salary, profession, and the emirates in which they lived in the UAE. Table 2 summarises the descriptive statistics for the total 601 responses: 280 (46.6%) females and 321 (53.4%) males. A majority of the female respondents were within the range of 25–35 years old (41.4%), followed by the age group of 18–24 (29.3%). Similarly, most men were within the age group of 25–35 (33.6%), followed by 36–45 years old (33.3%). Most respondents held a bachelor's degree, followed by those with only a high school degree (48.6% and 33.8%, respectively). Correspondingly, most of the respondents' wages were within the range of AED 0–4999 by (59%). In terms of occupation, most of the respondents (63.2%) were paid on a salary basis. Regarding the emirates' distribution, most male and female respondents were from Dubai (41.1%), followed by Abu Dhabi (34.6%) and Sharjah (12%). Table 2 is divided into male and female sections to determine whether the demographic data collected matched the government-provided demographic data [49] and whether the sample collected was nearly identical to the population.

Table 2. The demographic composition of the samples (*N* = 601).

Demographic Question	Options	What Is Your Gender?			
		Female		Male	
		Count	N%	Count	N%
What is your age?	18–24	82	29.30%	59	18.40%
	25–35	116	41.40%	108	33.60%
	36–45	64	22.90%	107	33.30%
	46–60	16	5.70%	43	13.40%
	61 or older	2	0.70%	4	1.20%
What is the highest level of education that you have completed?	Less than high school	9	3.20%	12	3.70%
	High school graduate	94	33.60%	109	34.00%
	Bachelor's degree	142	50.70%	150	46.70%
	Master's degree	33	11.80%	43	13.40%
	Doctorate	2	0.70%	7	2.20%
What is your approximate average household income in AED?	0–4999	176	62.90%	179	55.80%
	5000–9999	49	17.50%	51	15.90%
	10,000–29,999	44	15.70%	43	13.40%
	30,000–49,999	7	2.50%	26	8.10%
	50,000 or above	4	1.40%	22	6.90%
What is your occupation?	Student	60	21.40%	30	9.30%
	Employed for wages	143	51.10%	237	73.80%
	Self-employed	26	9.30%	33	10.30%
	Retired	3	1.10%	3	0.90%
	Unemployed	48	17.10%	18	5.60%
What is your emirate?	Abu Dhabi	99	35.40%	109	34.00%
	Dubai	114	40.70%	133	41.40%
	Sharjah	31	11.10%	41	12.80%
	Ajman	21	7.50%	21	6.50%
	Ras Al Khaimah	7	2.50%	6	1.90%
	Umm Al Quwain	3	1.10%	3	0.90%
	Fujairah	5	1.80%	8	2.50%

4.2. Measurement Model Evaluation (the Outer Model)

The first step in analysing the reflecting measurement model was to determine the outer loading of the indicators. The outer loading should be equal to 0.7 or above, as recommended by [46]. Generally, indicators with an outer loading of 0.40 to 0.70 should be evaluated for deletion only when doing so enhances the construct's internal consistency, reliability, or convergent validity. In contrast, indications with an outer loading of less than

0.40 should always be eliminated [46]. In Table 3, the outer loading for BMU1 = 0.257 was deleted, which enhanced AVE from 0.501 to 0.611. Nevertheless, the items (EC2 = 0.495, EC1 = 0.683, and BMU2 = 0.581) were not deleted, as all those items were in the acceptable value >0.4. Moreover, deleting them would not enhance the AVE or Cronbach's alpha values. Second, the PLS-SEM analysis in Table 3 demonstrated that the composite reliability and Cronbach's alpha values for the constructs were >0.7; those criteria ranged from 0.757 to 0.883 and 0.805 to 0.919, respectively. As a result, the internal consistency of the study framework model was established. Third, as shown in Table 3, all questions assessed a single concept, and the average variance extracted (AVE) value was more than 0.5, indicating that convergent validity was confirmed.

Table 3. Result summary for the measurement model.

Latent Variable	Indicators	Convergent Validity		Internal Consistency Reliability Validity		Discriminant Validity
		Loading	AVE	Cronbach's Alpha	Reliability	HTMT
		>0.70	>0.50	0.60–0.90	0.60–0.90	Significantly < 0.85
Mobile users' knowledge and skills to perform the behaviour (MU_KSP)	KSP 1 KSP 2 KSP 3 KSP 4	0.832 0.874 0.870 0.865	0.740	0.883	0.919	YES
Mobile users' salience of behaviour (MU_SB)	SB 1 SB 2 SB 3 SB 4	0.798 0.817 0.788 0.834	0.655	0.834	0.884	YES
Mobile users' environmental constraints (MU_EC)	EC 1 EC 2 EC 3 EC 4	0.683 0.495 0.811 0.838	0.518	0.757	0.805	YES
Mobile users' habit (MU_H)	H1 H2 H3 H4	0.798 0.770 0.711 0.848	0.614	0.801	0.863	YES
Behaviour of mobile users (BMU)	BMU1 BMU2 BMU3 BMU4 BMU5	0.257 0.581 0.876 0.832 0.805	0.611	0.783	0.860	YES

The fourth step in the outer model was to measure the discriminant validity, which was determined using the Fornell-Larcker criteria. The square root of the AVE of each construct should be higher than the correlation coefficient of any other construct [46,50,51]. Table 4 confirms that the Fornell-Larcker criteria were established as the square root of the AVE value was greater than the row and column values relating to them, which further validates the discriminant validity.

Table 4. Fornell-Larcker criteria.

	BMU	MU_EC	MU_H	MU_KSP	MU_SB
BMU	0.782				
MU_EC	−0.137	0.719			
MU_H	0.251	−0.470	0.783		
MU_KSP	0.201	−0.400	0.713	0.860	
MU_SB	−0.126	−0.239	0.383	0.440	0.809

Another approach used in PLS-SEM was the Heterotrait-Monotrait ratio (HTMT) of the correlations to appropriately measure discriminant validity. The HTMT technique estimates the genuine correlation between two constructs. The HTMT values in Table 5 showed that all constructs did not surpass 0.85, indicating that no discriminant validity was discovered. The result of the previous measurement analysis demonstrated the reliability and validity of the construct measurements. Therefore, the next stage for evaluating the structural model's outputs could proceed.

Table 5. Heterotrait-Monotrait Ratio (HTMT).

	BMU	**MU_EC**	**MU_H**	**MU_KSP**	**MU_SB**
BMU					
MU_EC	0.132				
MU_H	0.284	0.605			
MU_KSP	0.234	0.497	0.841		
MU_SB	0.167	0.355	0.511	0.520	

4.3. Structural Model Evaluation (the Inner Model)

The first step in assessing the structural model was to analyse the possibility of collinearity between each set of constructs. The VIF values in PLS-SEM should be less than 3 to ensure that collinearity has no significant effect on the structural model assessment [46]. By analysing the inner VIF values in SmartPLS, it was found that MU_EC (VIF = 1.301), MU_H (VIF = 2.237), MU_KSP (VIF = 2.197), and MU_SB (VIF = 1.258). All of the predictor constructs had a VIF value less than 3, indicating that collinearity between items was not a problem in the structural model. The second step in inner model assessment was to determine the significance and relevance of the structural model's relationships by calculating the beta values (β) of the path coefficients. Figure 2 illustrates the path coefficient from the constructs to the mobile users' behaviour with the *p* values calculated for the structural model's relationships. The highest path coefficient was related to MU_SB ($\beta = -0.289$; $p < 0.000$) with a negative direction, followed by MU_H ($\beta = 0.248$; $p < 0.000$), MU_KSP ($\beta = 0.138$; $p < 0.05$), and finally MU_EC ($\beta = -0.041$; $p > 0.05$) to the negative direction. To conduct the hypotheses testing and check whether these relationships are significant, the study performed a bootstrapping technique using 10,000 bootstrap samples by selecting the complete bootstrapping option. Figure 2 also shows the *p* values associated between each construct and BMU. Table 6 summarises the *t* value, *p* value, and the 95% confidence interval computed using the percentile technique. This indicated that all associations for the structural model's hypotheses H1, H2, and H4 were statistically significant, except for H3, which was rejected. This rejection was also supported by *p* value = 0.585, which was > 0.05.

The third part of assessing the structural model was to calculate the coefficient of determination (R^2) value to estimate the model's explanatory power. Figure 2 shows the R^2 value for the endogenous construct (BMU) with the substantial value = 0.131. However, according to Hair Jr, Hult, Ringle and Sarstedt [46], the greater the number of predictor constructs, the higher the R^2 value. The R^2 value should always be interpreted in light of the context of the study; for example, the R^2 values in a model predicting human attitudes, perceptions, and intentions are doubtful. The final step was to measure the predictive relevance Q^2 value using the blindfolding procedure in SmartPLS. It was found that Q^2 was greater than zero for the construct (BMU) = 0.073. Through the Q^2 statistics, it was shown that there was sufficient predictive relevance for the indicators of the endogenous construct in the structural model.
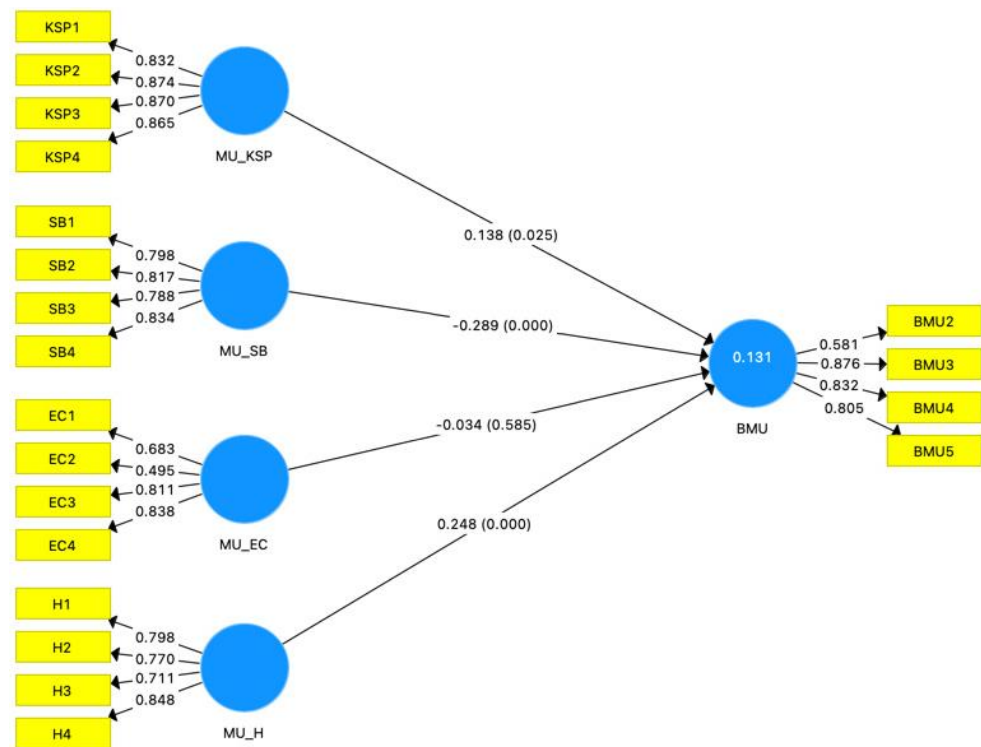
Figure 2. The structural equation model with factor loading value and R square.

Table 6. Significant testing results of the structural model's path coefficients.

Structural Path	(β)	t Value	*p* Value	95% Confidence Interval	Conclusion
MU_KSP -> BMU	0.138	2.246	0.025	[0.017, 0.259]	H1, Supported
MU_SB -> BMU	−0.289	4.374	0.000	[−0.391, −0.136]	H2, Supported
MU_EC -> BMU	−0.034	0.547	0.585	[−0.147, 0.139]	H3, Not Supported
MU_H -> BMU	0.248	4.045	0.000	[0.123, 0.363]	H4, Supported

5. Discussion

Using an IBM-based model, this study examined the possible determinants that contribute to the sustainability of recycling behaviour. The study did not concentrate on behavioural aspects since those have been covered often in research [11,12,52–55]. The IBM variables demonstrated a major good influence on the medical field in terms of maintaining behaviour continuity in order to continue addressing the treatment [17]. The purpose of this research was to determine whether those elements might have a beneficial effect on the sustainability of smartphone recycling behaviour. Considering the R^2 value, the findings justified the adoption of this frame = 0.131 for stock returns research or this study's subject. Usually, for reverse logistics (RL) and collection of smartphones from customers, the R^2 value was as low as 0.10, which was considered acceptable [46]. The study found that the smartphone users' knowledge and skills (H1) positively contributed to a continuous smartphone recycling behaviour. This result was consistent with the findings by [12] that focused on "ecological knowledge (eco-literacy)", although their research concentrated on the impact on the intention in the Decomposed Theory of Planned Behaviour (DTPB). Similarly, the current study's result was aligned with the study by [31], in which they found that people with high education and knowledge of environmental preservation and conservation had more inclination to participate in recycling behaviour as they were even willing to pay for recycling.

For the second hypothesis (H2) on examining whether the salience of recycling behaviour is positively associated with continuous smartphone recycling behaviour, the results showed a significant influence on the behaviour. Nevertheless, it was surprisingly

towards the negative direction, meaning that the more salience in a behaviour, the less the intention to perform the behaviour continually. The study's result interestingly contradicted the results by [20], who argued that increasing the salience of product transformation— which involved recyclables being transformed into new items—led to the increase in recycling behaviour. Moreover, the results did not match the findings of [32], who examined the IBM factors to check which factor could predict nurses' intentions to deliver "as required" pain relief medications. They found that salience of behaviour was the only significant predictor for the nurses' intentions. The possible explanation for this study's results is that the respondents might not understand the survey questions' links between the importance of the behaviour and performing the behaviour, or they did not consider salience of behaviour as important to the satisfaction of doing the behaviour continually.

The third hypothesis (H3), regarding whether removing the environmental constraints will positively contribute to continuous mobile phone recycling, was found to be not significant. The results were not in line with the findings by [33], in which environmental constraints were alluded to by the authors as issues that impeded patients from adhering to a pharmaceutical regimen. Nevertheless, the results were consistent with the findings by [34], who also found that environmental constraints to performing green behaviour did not create barriers for green buyers to achieve their individual sustainable goals. This result was expected in the UAE as it is rare to find environmental barriers that might impact mobile users' sustainable recycling behaviour. The government even created an organisation called "Tadweer", responsible for waste management with a customer hotline for collecting any kind of waste or e-waste. Moreover, the UAE government built multiple places and channels for collecting e-waste for recycling.

Finally, regarding the habit factor (H4) on whether it positively contributes to continuous smartphone recycling behaviour, the results confirmed that habit was the top factor that contributed to recycling behaviour sustainability. This result could be compared to the one determined by [10], who found that young adults' recycling habits were a strong predictor of their intention to recycle e-waste. While Aboelmaged's (2021) research focused on the influence of habit on intention and the current study on behaviour sustainability, the concept is similar, particularly given that his study was done in the UAE. Nevertheless, this study's result was not in line with the findings by [56], who measured habit as a positive intention to repurchase. This author discovered that habit did not affect the intention to buy a refurbished smartphone. This research placed greater emphasis on the customers' decision to acquire a refurbished phone, while in contrast, the current study placed greater emphasis on returning or refurbishing used mobile phones.

Theoretical and Practical Implications

TPB is a practical theory for explaining recycling behaviour and has been used and examined in numerous research and fields. The power of this theory lies in its capacity to allow for an extension of variables (as highlighted in the previous sections) for a better understanding of mobile consumer behaviour. Notably, DTPB is already an extended version of the theory [12,57]. Therefore, to propose a new extension, the factors should be kept within the TPB theory. Similarly, IBM was initially designed to assist the medical sector in predicting health behaviours and recommending preventive measures [27,28]. The IBM framework was mostly implemented in the health sector, as presented in the previous sections. Therefore, before using the IBM framework as a core theory for any new study like recycling, it is essential to measure the new factors (knowledge and skills, salience of recycling behaviour, environmental constraints, and habits) used by this IBM model with a proven model like TPB in the field of recycling. This research helped examine IBM factors relating to e-waste recycling in general and smartphones in particular. That is the primary contribution of this study, which may serve as a springboard for future research, including the use of IBM as a comprehensive framework relating directly to recycling behaviour. As for practical implications, this study will assist smartphone firms in focusing more on knowledge and habit factors to increase the number of returned devices.

6. Conclusions

Recycling is the most efficient way to manage e-waste, particularly smartphones, since they are expensive products with short lifetimes. Additionally, the most commonly used pattern for such gadgets is to keep them rather than sending old devices for recycling. As a result, sustaining recycling practices is very difficult when it comes to cell phones. This research surveyed a representative sample of respondents using an online survey to determine the factors that contribute to the sustainability of smartphone recycling behaviour, by analysing the influence of IBM-related variables (knowledge, salience of behaviour, environmental constraints, and habits). The research will encourage industry players to prioritise such factors in their reverse logistics system to encourage mobile users to continue returning EOL/EOU smartphones, which will significantly decrease mobile waste and improve natural resource optimisation.

Limitations and Future Research

This paper examined only four factors from IBM. Future studies are recommended to study the complete IBM framework in the e-waste recycling field to achieve sustainable performance, particularly examining the variables that affect behavioural intention. Moreover, this study was conducted in the UAE. Researchers can adapt the research paradigm to other countries. Limitations were observed for the questions related to the salience of behaviour, which can be improved in the future by using a qualitative approach through interview questions that are more evident to the respondents, besides conducting a mixed-method methodological choice.

Appendix A

Table A1. The questionnaire items.

Indicator or Variables	Questions	Scale
Actual knowledge	I have the knowledge regarding what kinds of e-waste can be recycled or reused.	1 = Fully disagree to 5 = Fully agree
	I have more of an idea about where I can return my mobile phone (locations and channels) for recycling.	
	I have enough information about when I should return my end-of-life mobile phone.	
	I have enough information about the recycling process and what will happen to my recycled mobile phone.	
Salience of behaviour	Having enough information about where to return an end-of-life mobile phone is important to me.	
	Having enough information about how I can return an end-of-life/end-of-use mobile phone to a producer or recycler is important to me.	
	Having sufficient information about the end of life of my mobile phone is critical to me (e.g., date/time of handover to producer or collector).	
	I know that end-of-life mobile phones may pollute the environment or endanger human health if not disposed properly.	

Table A1. *Cont.*

Indicator or Variables	Questions	Scale
Environmental constraints	Electronic waste recycling is someone else's responsibility.	1 = Fully disagree to 5 = Fully agree
	The recycling collection sites are far and I do not have reliable transportation.	
	I do not have the time to recycle my end-of-life/end-of-use mobile phone.	
	I think that sending my end-of-life/end-of-use mobile phone for recycling is costly.	
Habit	I like what I know about mobile phone recycling rather than getting to know new things.	
	Recycling general waste is my daily routine.	
	I always follow the same action regarding my end-of-life/end-of-use mobile phone (e.g., stockpiling, recycling, resale, etc.).	
	I have previously engaged in the practice of recycling or returning my old mobile phone to the manufacturer.	
Behaviour of mobile users	I used to separate recyclable items from general waste.	1 = Never to 5 = Always
	During the previous month, I have done more recycling than I usually do.	
	During the last three months, I have recycled my old mobile phone at a specific collection point specific to electronic waste.	
	During the last three months, I have recycled my old mobile phone after receiving cash incentives from the phone producer or municipality.	
	I discarded my previous mobile phone three months ago after the phone manufacturer/municipality deleted my data.	

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