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Assessing the Measurement Model for Source-Separating Waste for Recycling under a Proposed Smart Waste Management Scheme in Shah Alam, Malaysia

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Abstract: Due to rapid urbanization, solid waste management (SWM) is a major challenge in Malaysia, hence the need to sustainably manage it. Compared with other states, Selangor produces the highest volume of domestic waste. Most of the state's waste is generated in Shah Alam City. This condition is expected to worsen because the population of Shah Alam is projected to rise by 2.5% from 2018 to 2035. This situation will increase the demand for resources, production, and consumption, increasing the volume of waste generated in Shah Alam. Hence, the pressing necessity to advance from the current traditional waste management practices to a more sustainable SWM system has been identified as a key target in Shah Alam's 2025–2030 plans. The Smart Waste Management System (SWMS) has been identified as a novel approach to dealing with the absence of route optimization, real-time information exchange, and the consequent increase in waste management costs. All of these elements have characterized the current traditional households' SWM. However, because this method is novel, there is a dearth of knowledge on the appropriate measurement model for evaluating the dimension of households' intention to recycle waste through source separation as well as measuring the determinants of such a pro-environmental intention under the new SWMS. Thus, confirmatory factor analysis (CFA) was carried out to verify the factorial structure of the variables, relying on the Theory of Planned Behavior (TPB) based on the structural dimensions identified in prior exploratory factor analysis (EFA). The study found support for the use of TPB as a relevant framework for modeling the intention for source separation and its determinants under SWMS.

Keywords: waste management; smart waste management; smart waste technology; smart recycling; smart cities; smart Selangor

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1. Introduction

Rapid urbanization is associated with the challenges of growing municipal solid waste (MSW) generation. The continuous rise in waste generation leads to several unfavorable health and environmental consequences, such as air pollution, greenhouse effects, and water contamination, among others. The increased pursuit of rise in economic growth by nations has resulted in improving the standard of living, purchasing power, and finally, an increase in population. These have significantly contributed to higher waste generation throughout the years, warranting the pressing need to sustainably manage waste [1,2]. Sustainable waste management refers to the process of collecting, transporting, recycling, and disposing of different types of waste without harming the environment, population, and future generations. Thus, recycling, which begins with the source separation of waste, is an important pillar of sustainable waste management.

In 2007, Malaysian households' daily waste generation was approximated at over 18,000 tons, while the population was estimated at 25 million [3]. Moreover, it was estimated that solid waste generation by 2020 would reach 30,000 tons daily, yet as early as 2012, its generation exceeded 33,000 tons per day [4–6]; and it is estimated to increase to as much as 49,670 tons per day by 2030 [7]. The continuous rise in waste generation requires further investment by the Malaysian government, especially in recycling.

It is worth noting that Selangor State produces the highest amount of domestic waste in Malaysia, and the majority of the state's waste is generated in its capital city, Shah Alam. As the capital of the state that generates the most waste, the Shah Alam authorities realized the importance of home segregation and recycling relatively earlier compared with other states. The first official source segregation program in Shah Alam started on 1 October 2015. Yet, these improvements are still considered somewhat unsuccessful due to the lack of participation by the majority of households in the city and the absence of enforcement of the source segregation program. This has created a strain on its landfills [8,9]. Another account that is expected to exacerbate this problem in the future is that Shah Alam's population is expected to grow by 2.5% annually from the present to 2035. This is creating a growing demand for its natural resources, with a continuous increase in its unsustainable production and consumption patterns. Thus, there is a pressing and inevitable need to improve the current traditional practices toward a more efficient and sustainable practice in order to protect the city's environment while minimizing generated waste [9]. Quite disturbing, albeit the unavailability of data, is that recent waste collection in Selangor shows that daily disposal in the state has risen to 7000 tons [10]. This is challenging as Shah Alam has the vision of achieving a 20% recycling rate by 2030 [9].

As such, this study evaluates Shah Alam households' intention to practice the Smart Solid Waste Management System (SWMS) as a promising method to deal with the shortcomings of the current traditional SWM challenges in the city. This study is one of the earliest social science research and economic valuation studies on the feasibility of introducing a smart waste management system in Malaysia, particularly in Shah Alam. This is timely, as the world now lives in the transition period toward the *smart* living concept [11]. The SWMS has the disadvantage of suboptimal routing cost due to a lack of real-time information sharing, thereby increasing waste transportation costs and, eventually, an overall increase in the budgetary cost of managing solid waste.

Hence, the main objective of this study is to assess the dimensions and appropriateness of the latent variable model for measuring households' intention to recycle waste through source separation as well as its determinants under the new smart waste management in Shah Alam. Previous empirical studies assessing the determinants of households' intention or willingness to recycle waste and its determinant have been based on attitude–behavior models. Earlier studies using attitude–behavior models relied on the theory of reasoned action (TRA) as the relevant theoretical framework for examining recycling and its determinants [12–15]. Meanwhile, more recent studies have instead adopted the theory of planned behavior (TPB) as a more appropriate theoretical framework [16–19]. The reason adduced for such accents on the superiority of TPB over the TRA is based on the latter's inclusion of a variable capturing respondents' perceived behavioral control.

2. Current Waste Management Practice in Shah Alam

Shah Alam faces a critical challenge in implementing sustainable waste management due to rapid urbanization and industrialization developments. Sustainable waste management denotes the collection, transportation, recycling, and disposal of different types of waste without harming the environment, population, and future generations. According to KDEBWM (Kumpulan Darul Ehsan Berhad Waste Management), the current waste collection in Selangor, including Shah Alam, is reported to be approximately 6000 to 7000 tons per day. Food waste alone contributes to approximately 40% of the total waste generated [10]. The characterization of solid waste shows huge potential for recycling because the highest percentage of waste generated is food waste at 42.34%, followed by plastic waste at 18.05%, diapers at 8.37%, and paper waste at 7.75%. Garden waste of 7.8% slightly exceeds the proportion of paper waste in Shah Alam, but does not constitute much of the policy concerns on recycling; in addition, the country's aggregate profile in Figure 1 shows the relevance of paper waste over garden waste in Malaysia.

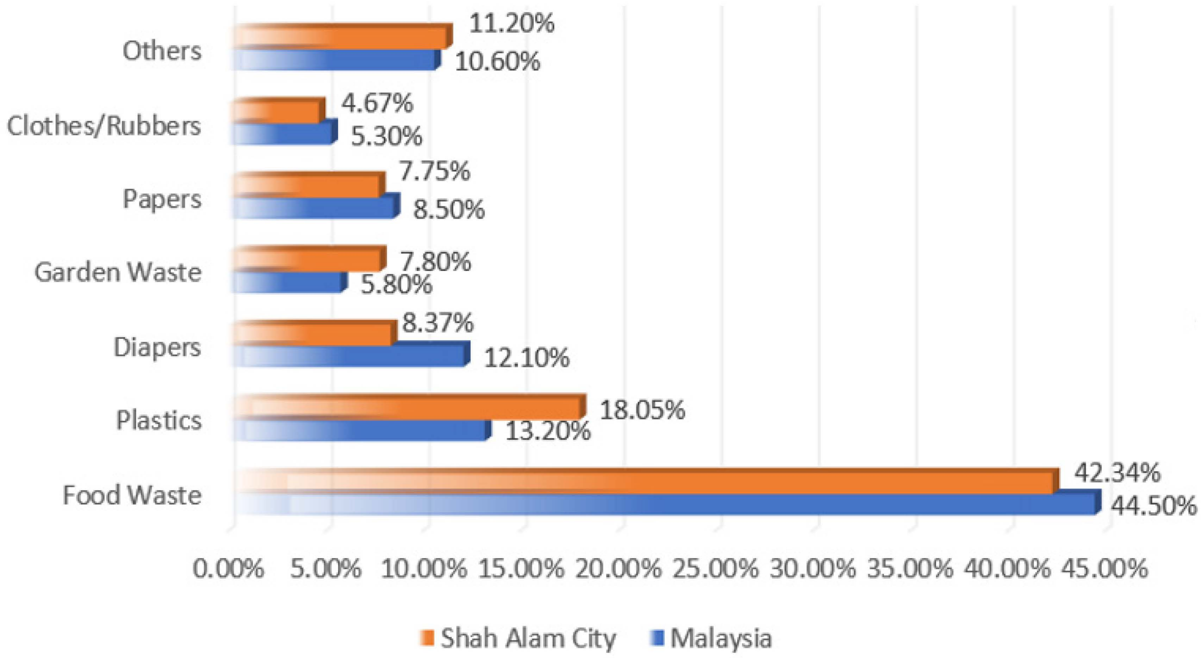

Figure 1. Household waste composition in Shah Alam City and Malaysia. Source: MBSA (2020).

It is worth mentioning that the Shah Alam City Council, locally known as MAJLIS BANDARAYA SHAH ALAM (MBSA), formerly managed waste management in Shah Alam. In 2011, the state government instructed the local authorities to acquire all SWM contracts from the previous contractor, Alam Flora Sdn. Bhd [20]. Following this change, the MBSA was responsible for monitoring the contractors assigned to manage the waste in the city. However, starting from March 2016, waste in Shah Alam has been managed by KDEB Waste Management (KDEBWM), which is a wholly owned subsidiary organization of Menteri Besar Selangor Incorporated (MBI). This organization was developed to manage domestic waste collection and public cleaning services in Selangor State [21]. The MBSA is one of twelve municipalities served by KDEBWM.

KDEBWM is committed to implementing smart and sustainable waste management practices in its territory. Currently, KDEBWM has deployed elements of SWMS in the form of an application called the iClean Selangor mobile application since 1 July 2016; the application is mainly targeted at solving the concerns of overflowing domestic bins. Specifically, iClean Selangor application users are able to download the application from the Google Play Store. After registration, users can update the contractors by distributing images of uncollected wastes to the command center for further action. Waste collection personnel will be alerted using a special application for collection purposes. To date, the application is used to monitor waste bin levels in 11 municipalities in Selangor.

However, beyond this pilot project, the application of SWMS is broader. According to Muniandy et al. (2018) [22], the operation of SWMS takes place through the Internet of Things (IoT) to allow waste managers to remotely monitor the bins in real-time from their computers via sensors installed in the bins. The sensors are built-in to measure the waste level, and indicators will be activated when the level gains a specified limit. These indicators guide waste collectors to optimize routing plans by collecting and transporting only waste bins flagged filled, thereby reducing collection costs through real-time information gathering and sharing. This conforms to Shah Alam's 2025–2030 plans, which include the introduction of a more robust SWMS to address the current challenges plaguing waste management in the city [8].

3. Theoretical Framework

Behavioral scientists acknowledge the difficulty in understanding the determinants of behavioral intention and actual behavior, much less estimating their determinants for actions such as recycling. Thus, various theoretical models have been developed in that context [23]. The theory of reasoned action, TRA [24,25], and its more refined version, the theory of planned behavior, TPB [26,27], have been widely used to analyze and assess the determinants of intention and behavior in the literature.

TPB is preferred to TRA due to its extension of the determinants of behavioral intention or actual behavior to capture a measure of an actor's (recycler's) volitional control over an intended action or its actual performance (i.e., recycling). The measure of volitional control is called perceived behavioral control (PBC). In the original manuscript by Ajzen (1985) [26], it measures an individual's perception of the extent of their control over performing an intended action (or behavior). However, many studies have extended it to assessing even behavioral intention, implying that an individual's perceived volitional control of an action determines even the intention to perform the action to begin with.

The theory suggests that the intention to engage in action (BI) is determined by attitude toward the behavior, subjective norm, and perceived behavioral control. At the same time, BI is the immediate antecedent of behavior. In theory, intention is defined as the motivational factors influencing behavior and the amount of work people are willing to put into performing that behavior. The three determinants proposed by the theory include the following: (a) Attitude (ATT) toward the behaviors, defined as the degree to which a person has a favorable or unfavorable affective or instrumental evaluation of the behaviors. (b) Subjective norm (SN) is defined as the perceived injunctive and descriptive social pressures to perform or not to perform the behaviors. (c) Perceived behavioral control (PBC) refers to the extent to which the individual perceives the behaviors at hand to be under his or her volitional control.

Thus, TPB suggests that if the attitude, subjective norms, and PBC towards a specific act are favorable, the more intention there will be to perform the behavior. Figure 2 depicts a schematic representation of the theory.

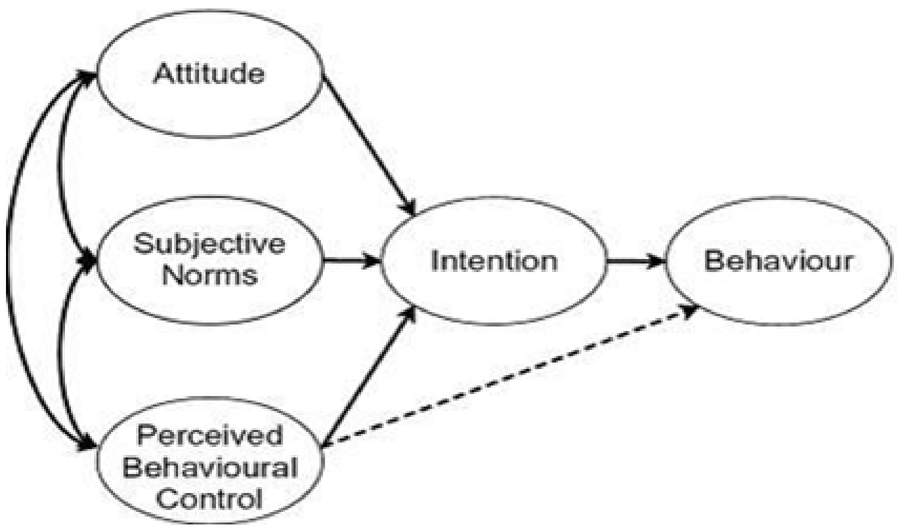

Figure 2. Theory of planned behavior.

4. Results and Discussion

4.1. Socioeconomic Characteristics of Households in Shah Alam

Table 1 shows the socioeconomic characteristics of respondents in the study area. A total of 12 questionnaires were deemed incomplete and unusable, thus only 432 were considered valid for analysis.

Table 1. Socioeconomic characteristics of respondents.

Variable	Frequency	Percentage
Sex		
Men	233	53.9
Women	199	46.1
Respondents' age		
18 to 28 years	113	26.2
29 to 39 years	195	45.1
40 to 50 years	88	20.4
51 to 61 years	29	6.7
62 years and above	7	1.62
Income category		
Low income: RM 0 to RM 4999 (B40)	78	18.1
Middle income: RM 6000 to RM 10,999 (M20)	223	51.6
High income: RM 11,000 to RM 20,000 and more (T20)	131	30.3
Educational qualification		
Diploma and below	227	52.5
Bachelor's degree and above	205	47.5
Marital status		
Single	144	33.3
Married	288	66.7
No. of observations	432	

4.1.1. Sex Distribution

Respondents' recruitment for the research did not consciously take an equal number of samples across sex into account. Nonetheless, the frequency across sex did not vary much as 53.9% of the respondents are men while 46.1% are women. This approximates the 2020 sex distribution data published by the Department of Statistics Malaysia (DOSM). According to the DOSM, the national sex distribution in 2020 stood at 52:48, while that of Selangor was 53:47 for men to women [28]. This finding is in line with the findings of Chinh et al. (2021) [29]. Chinh recorded more male respondents than female but without a huge disparity either. The approximately equal proportion of sex distribution makes the model more representative across sex.

4.1.2. Age of Respondents

As evident from Table 1, the average age of respondents in the study area is 34.71 years old (approximately 35). This shows the majority of the respondents for the study are drawn from the productively active age bracket. The age of potential smart solid waste services consumers in the area ranges from 18 to 80 years of age.

4.1.3. Income Category

Because subscription to the SWMS requires paying more money, generally, it would be expected that an individual with a higher income is more likely to subscribe to the smart solid waste management system than low-income individuals. From the socioeconomics category in Table 1, following the Malaysian government classification of B40 for low-income, M40 for middle-income, and T20 for high-income, as many as 51.6% of the respondent are middle-income earners, and 30.3% are high-income earners, the remaining 18.1% are low-income earners. This indicates that respondents from the study area are mainly average-income earners. Understanding this income distribution is important as

Abdrabo (2008) [30], among others, reported a significant relationship between income and willingness to subscribe to improved solid waste collection.

4.1.4. Educational Qualification

The distribution of respondents by educational attainment within the study area shows that 52.5% of the respondents have a diploma and below as their highest education level, while 47.5% of respondents have a bachelor's degree and above. It would be valid to say that virtually all respondents in the study area are educated but differ by the highest education obtained. This would make advocacy programs on SWMS easier to organize.

4.1.5. Marital Status

The distribution of marital status of respondents from the data collected from the study area shows that married individuals are more than single individuals. The data summary shows that 66.7% of the respondents are married while 33.3% are single. These statistics slightly vary from the national distribution of the population by marital status. According to the Malaysian Department of Statistic (DOS), 55.5% of matured Malaysian were married in 2020, while the remaining 45% have either never married, divorced/separated, or widowed [28]. This implies that married households have been slightly oversampled above the national proportion. This is not expected to cause serious statistical problems as each group is sizably captured. This variable is important because marital status distribution explains the willingness to subscribe to improved solid waste management [31].

4.2. Exploratory Factor Analysis (EFA) of Latent Variables

To guide in estimating the measurement model, all latent factors were explored for dimensionality and sample size adequacy using the component factor model of EFA and reliability. The latent variables subjected to EFA in accordance with the TPB include the intention to practice smart solid waste management for separate solid waste categories, attitude toward implementing smart solid waste management, as well as subjective norm/social influence on smart solid waste management and perceived behavioral control related to smart solid waste management. However, given the large number of indicators used, including all-in-one analysis, which generates results in a single table, would render the display awkward. This is evident as even the display of the dimensionality of intention to separate waste in Tables A1 and A2 was huge. Hence, the EFA for each of the respective latent variables was separately examined in turn.

4.2.1. Factor Analysis of Households' Intention to Engage in Smart Solid Waste Management for Separate Waste Categories

Table A1 in Appendix A shows the correlation matrix for all seventeen (17) items (questions) measuring the different dimensions (categories) of solid waste separation by households in Shah Alam. Because the dimensions of the table are huge, Table A2 was included to capture the descriptors for the leading column and row. The results show the fulfillment of the factorability requirement of the dominance of the correlation matrix with a bivariate coefficient equal to and greater than 0.3, the individual item sample size adequacy measures were all greater than the threshold of 0.6. Overall, items' sample adequacy (KMO) was estimated at 0.851, greater than the minimum threshold of 0.6, and Bartlett's test of sphericity is statistically significant at a 1% level (less than 0.05 threshold). These confirm the appropriateness of all items for factorability [32,33]. The results presented in Table 2 show the respective eigenvalue, the variance of waste separation explained by each dimension, and the reliability of each dimension based on Cronbach's alpha measure. In addition, the communalities (threshold of at least 0.3) and factor loadings (threshold of at least 0.4) of all items are within the acceptable values.

Table 2. Four-factor structure for intention to practice smart solid waste management for separate solid waste categories.

	Components					
	Paper Waste	**Diaper Waste**	**Organic Waste**	**Plastic Waste**	**(Communalities)**	**Mean (Std. Dev.)**
Cardboards	0.842				0.895	4.09 (1.090)
Used calendars	0.822				0.939	3.64 (1.327)
Wrapping papers	0.812				0.933	3.47 (1.374)
Paper cartons	0.801				0.914	3.45 (1.400)
Magazines/News papers	0.762				0.750	3.48 (1.411)
Reusable children diaper		0.913			0.919	2.43 (1.265)
Disposable children diaper		0.902			0.904	2.44 (1.255)
Disposable adult diaper		0.899			0.908	2.45 (1.302)
Reusable adult diaper		0.892			0.874	2.44 (1.271)
Food leftovers			0.878		0.904	4.25 (0.843)
Organic kitchen waste			0.869		0.853	4.20 (0.862)
Plant and flower trimmings			0.773		0.933	3.48 (1.113)
Domestic vegetal waste			0.772		0.935	3.47 (1.117)
Plastic (pet) bottles				0.905	0.911	4.58 (0.534)
Plastic shopping bag				0.891	0.883	4.47 (0.736)
Used plastic utensils				0.625	0.489	4.16 (0.834)
Plastic packaging/wrapping				0.595	0.532	4.58 (0.534)
Cronbach's alpha	0.878	0.796	0.958	0.968		
Eigenvalues (% of variance)	7.757 (45.63)	3.441 (20.243)	2.147 (12.628)		1.131 (6.654)	

All the dimensions established sufficient Cronbach's alpha, with 0.878 for paper waste, 0.796 for diaper waste, 0.958 for food and organic waste, and 0.968 for plastic waste, and all are greater than the minimum threshold of 0.7, as suggested by (Hair, 2009) [34]. This justifies the internal consistency of all items included in the scale to measure households' willingness to practice waste separation under the proposed smart solid waste management. Furthermore, the communalities' minimum thresholds of 0.3 have been met across the dimensions, as they are above 0.3 [32]. This means that more than 30% of the variation in an item is collectively explained by other items or the associated latent factor. This further justifies the outcome of the correlation matrix, which shows that items are significantly intercorrelated with each other.

Similarly, the results of the eigenvalues of each dimension, as shown in the table, demonstrate that the factor model cumulatively explains up to 85.2% of the total variation in households' willingness to separate waste into the four categories under the proposed SWMS. Each dimension has 45.6%, 20.2%, 12.6%, and 6.6%, respectively, for paper waste, diaper waste, organic waste, and plastic waste.

4.2.2. Factor Structure for Attitude

Households' attitude to engage in the separation of solid waste under a smart solid waste management system was also assessed based on the importance of "attitude" in explaining psychological willingness to engage in an action (smart solid waste management system), as proposed by the TPB. The result of the EFA for the attitude variable presented in Table 3, as theorized based on the TBP result, shows the factor model for attitude toward smart solid waste separation has a single dimension, as indicated by the eigenvalue of 2.416, and the factor explains up to 60.40% of the variations in the latent attitude variable.

Table 3. Factor analysis of households' attitude toward separating solid waste under smart solid waste management.

Questionnaire Item	Mean (Std. Dev.)	Components (Communalities)	Correlations and Sample Size Adequacy			
Adopting smart SWM to recover useful resources is a good idea.	6.36 (0.806)	0.848 (0.59)	0.812 [a]			
Adopting smart SWM practice will be fun.	6.4 (0.768)	0.797 (0.719)	0.509 ***	0.713 [a]		
I would like a policy enforcing smart SWM to reduce the cost of waste management.	6.34 (0.831)	0.768 (0.636)	0.488 ***	0.611 ***	0.732 [a]	
I will support the implementation of smart SWM to reduce environmental pollution.	6.52 (0.74)	0.686 (0.471)	0.389 ***	0.47 ***	0.344 ***	0.804 [a]
Cronbach's alpha		0.779				
Eigenvalues (% of variance)		2.416 (60.396)				
KMO (Bartlett's test of sphericity)		0.755 (483.442 ***)				

a = sample adequacy, and *** denotes significance at 1%.

All the questions that addressed the latent factor established good measures as the Kaiser–Meyer–Olkin (KMO) measure of sample adequacy ranges from 0.71 to 0.81, which is greater than the minimum threshold of 0.6. On the other hand, Bartlett's test of sphericity is 0.75 with a 1% significant level. Meanwhile, the correlation matrix demonstrates all the items are highly correlated. Additionally, the component and communalities are appropriate in accordance with the thresholds mentioned earlier. The Cronbach's alpha, as suggested by Kline (2015) and Hair et al. (2013), is 0.78 [35,36]. The result implies that attitude as a latent construct is descriptively reliable.

4.2.3. Factor Structure for Subjective Norm

The TPB proposes that every action, such as the practice of smart solid waste separation, may not be predicted entirely by an individual's attitude but also by subjective norms. The variable, otherwise known as social influence, implies that individuals act according to the approval of their immediate social groups, such as peers, friends, family members, and other acquaintances who influence their actions. Subjective norms with respect to smart solid waste separation imply how others in society view this act. Do they approve of it or not? The EFA findings for the subjective norm component are depicted in Table 4. The result yields an eigenvalue of 3.682, which shows, in conformity to the theory, that the factor model has a single dimension that accounts for up to 92.1% variation in the latent variable.

Table 4. Factor analysis of households' subjective norm to separate solid waste under smart solid waste management.

Questionnaire Item	Mean (Std. Dev.)	Components (Communalities)	Correlations and Sample Size Adequacy			
I feel there is a good sense of community where I live	5.813 (0.985)	0.952 (0.907)	0.889 [a]			
I will be more encouraged to adopt smart SWM when a lot of people around me are practicing smart SWM	5.81 (0.995)	0.966 (0.933)	0.899 ***	0.854 [a]		
Most people I know would be willing to adopt smart SWM to manage their solid waste	5.803 (0.980)	0.96 (0.922)	0.887 ***	0.897 ***	0.881 [a]	
Most people I know would not think smart SWM practice will disregard my social status	5.817 (0.986)	0.959 (0.920)	0.86 8 ***	0.911 ***	0.902 ***	0.866 [a]
Cronbach's alpha		0.971				
Eigenvalues (% of variance)		3.682 (92.058)				
KMO (Bartlett's test of sphericity)		0.872 (2359.19 ***)				

a = sample adequacy, and *** denotes significance at 1%.

The EFA measures, such as KMO, Barlett's test of sphericity, correlation matrix, component, and communalities, are deemed adequate. The correlation reveals that there is a strong link between the items. All communality values are above the set minimum value of 0.3, the KMO exceeds the minimum threshold of 0.6, and Barlett's test of sphericity yielded a significant result at 1%. Additionally, the items estimated a Cronbach's alpha of 0.971, which indicates they are reliable and consistent in measuring the latent variable.

4.2.4. Factor Structure for Perceived Behavioral Control

The EFA results for PBC on the intention to separate solid waste under the smart waste management system in Shah Alam are shown in Table 5. According to the component model, PBC has a single dimension and explains up to 51.6% of the total variations in the latent variable, as indicated by the eigenvalue outcome of 2.578.

Table 5. Factor analysis of households' perceived behavioral control to separate solid waste under smart solid waste management.

Questionnaire Item	Mean (Std. Dev.)	Components (Communalities)	Correlations and Sample Size Adequacy				
It is easy for me to practice smart SWM as my family is always there to assist when I am busy.	6.36 (0.828)	0.803 (0.388)	0.846 [a]				
I can entirely determine whether to adopt smart SWM or not.	6.3 (0.816)	0.765 (0.645)	0.352 ***	0.755 [a]			
Smart waste management is not too different from my current waste handling practice.	6.29 (0.807)	0.712 (0.585)	0.308 ***	0.574 ***	0.770 [a]		
I will be encouraged to adopt smart SWM if it reduces my assessment tax.	6.39 (0.841)	0.673 (0.453)	0.311 ***	0.419 ***	0.391 ***	0.850 [a]	
Adopting smart SWM will not take too much of my time.	6.4 (0.814)	0.623 (0.506)	0.358 ***	0.458 ***	0.408 ***	0.326 ***	0.830 [a]
Cronbach's alpha		0.762					
Eigenvalues (% of variance)		2.578 (51.555)					
KMO (Bartlett's test of sphericity)		0.800 (492.52 ***)					

a = sample adequacy, and *** denotes significance at 1%.

All factorability indices aforementioned are within the acceptable range. The communality values are more than the recommended minimum requirement of 0.3. The KMO is 0.8, and Barlett's test of sphericity is significant at 1%. Furthermore, the items' estimated Cronbach's alpha of 0.762 means they are dependable and internally consistent. For that reason, PBC is deemed descriptively reliable and has a single latent factor structure.

EFA results for all latent variables of TPB specified to evaluate Shah Alam households' intention to participate in waste source separations under the proposed smart waste management system are descriptively reliable. However, EFA does not have the capability of determining the validity of all the variables. In addition, EFA lacks the capacity for theory testing of TPB with respect to the assessment of the convergent and discriminant validity for attitude, subjective norm, and PBC on households' intention to participate in waste source separations under the new smart waste management. To assess this, the EFA results are subjected to CFA, which will allow the validation of the variables; a requirement that must be fulfilled prior to the estimation of the functional relationship between the latent variables.

4.2.5. Factor Structure for Perceived Behavioral Control

The CFA, unlike the EFA, allows for empirical testing of the validity of factors before assessing the functional relations between the latent variables using the structural equation model (SEM). Accordingly, the validity of the measurement model with latent variables based on Figure 5, consistent with the EFA findings, was assessed through the convergent and discriminant validities as suggested by Hair et al., (2013) [35]. Such validity is not applicable to directly observable variables. Based on measures of households' willingness to separate the four different policy-relevant categories of waste disposed of by households and responses to the other three variables of TPB, including attitude, PBC, and subjective norm, a seven-factor measurement model was estimated for the assessment of convergent and discriminant validities via CFA. The results are shown in Table 6, as illustrated in Figures 3 and 4.

Table 6. Standardized and unstandardized estimates from CFA.

Items		Latent Variables	Estimated Coefficients		S.E.	C.R.	P
			Standardized	Unstandardized			
DSEG1	<---	Daiper_Waste__Separation	0.934	1			
DSEG2	<---	Daiper_Waste__Separation	0.958	1.017	0.025	41.001	***
DSEG3	<---	Daiper_Waste__Separation	0.929	1.024	0.028	36.210	***
DSEG4	<---	Daiper_Waste__Separation	0.951	1.023	0.025	40.600	***
PASEG2	<---	Paper_Waste__Separation	0.910	1			
PASEG3	<---	Paper_Waste__Separation	0.991	1.128	0.026	43.249	***
PASEG4	<---	Paper_Waste__Separation	0.987	1.144	0.027	42.507	***
FSEG3	<---	Food_Waste__Separation	0.489	1			
FSEG4	<---	Food_Waste__Separation	0.983	1.012	0.021	49.200	***
PSEG4	<---	Plastic_Waste__Separation	0.991	1			
PSEG2	<---	Plastic_Waste__Separation	0.911	2.569	0.483	5.321	***
FC5	<---	Perceived__Behavioral__Control	0.963	1			
FC4	<---	Perceived__Behavioral__Control	0.973	1.018	0.018	56.207	***
FC3	<---	Perceived__Behavioral__Control	0.595	0.63	0.042	14.949	***
FC2	<---	Perceived__Behavioral__Control	0.977	1.046	0.018	57.678	***
FC1	<---	Perceived__Behavioral__Control	0.984	1.039	0.017	61.331	***
ATT4	<---	Attitude_Smart__Waste	0.975	1			
ATT3	<---	Attitude_Smart__Waste	0.847	0.886	0.03	29.967	***
ATT2	<---	Attitude_Smart__Waste	0.940	0.952	0.021	44.961	***
ATT1	<---	Attitude_Smart__Waste	0.909	0.904	0.023	38.494	***
SI4	<---	Social__Influence	0.857	1			
SI3	<---	Social__Influence	0.835	0.967	0.044	22.216	***
SI2	<---	Social__Influence	0.936	1.101	0.041	27.097	***
SI1	<---	Social__Influence	0.869	1.023	0.043	23.860	***

*** Denotes Significant at 1%.

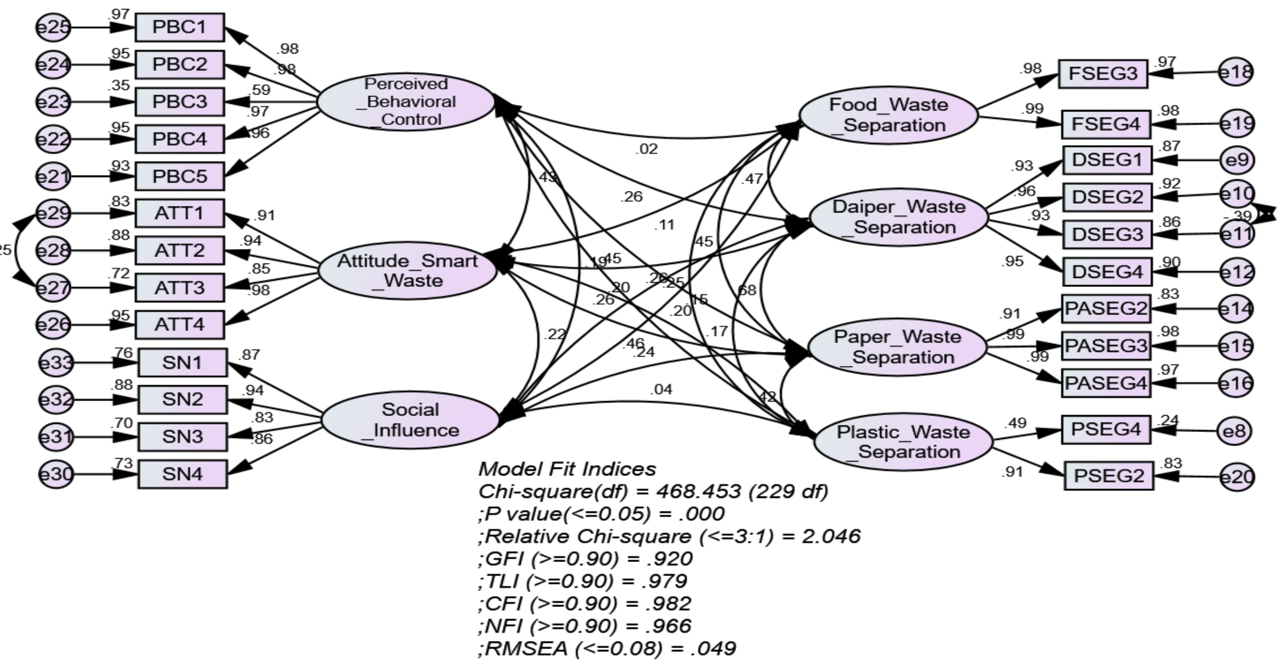

Figure 3. Standardized measurement model using CFA.

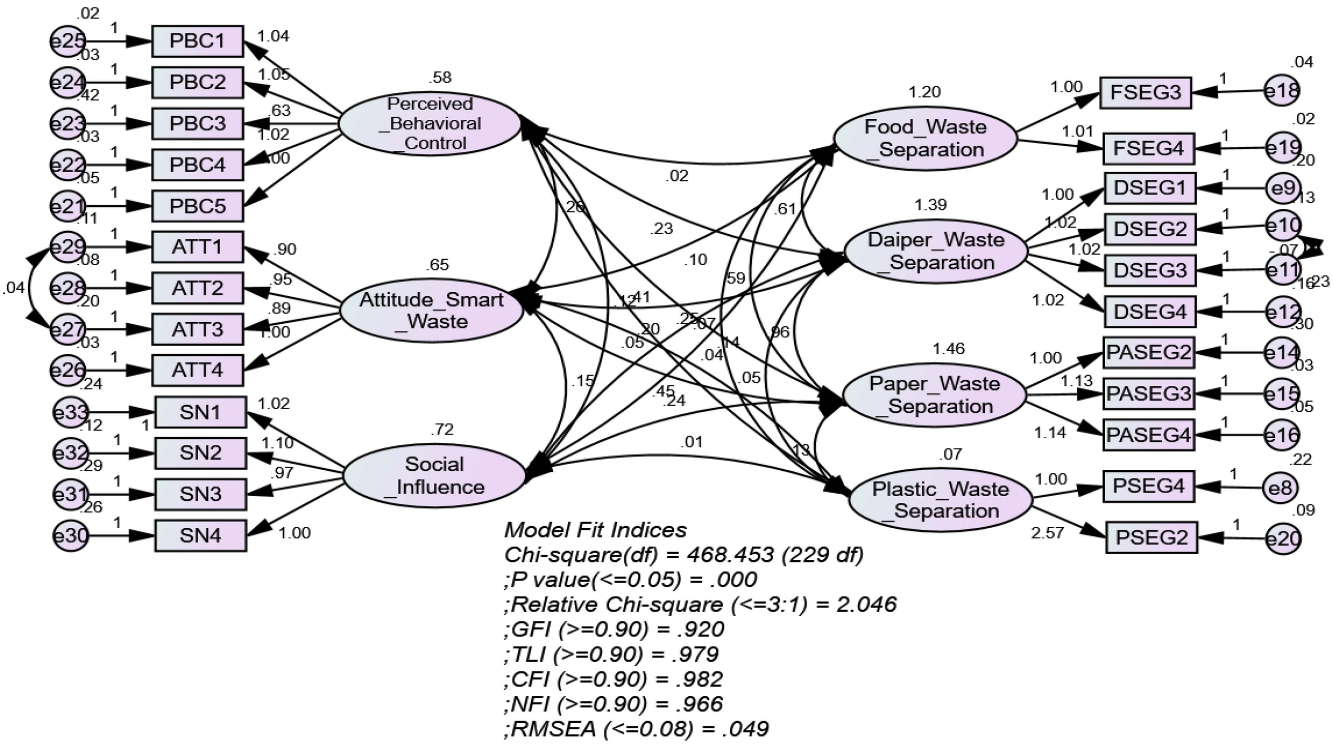

Figure 4. Unstandardized measurement model using CFA.

The CFA results shown in Table 6 reveal that all items are adequately loaded with no hay-wood estimates [35], which implies that no standardized estimates are greater than one and no negative estimates are observed between factors and their respective items (indicators or questions). In addition, all items were found to be statistically significantly loaded on their respective factors at a 1% level of significance. Figure 3 (standardized estimate) and Figure 4 (unstandardized estimates) show the values of the fit indices, which are considered the relevant statistical diagnostics for determining the appropriateness of the estimated measurement model.

The diagnostic fit indices estimated include, firstly, the absolute fit indices such as chi-square, relative/normed chi-square, root mean square error of approximation (RMSEA), and goodness of fit statistic (GFI). Secondly, incremental fit indices comprising the normed fit index (NFI), Tucker–Lewis index (TLI), and comparative fit index (CFI) were also estimated. It can be observed that the RMSEA value is 0.049, which is within the acceptable thresholds of less than or equal to 0.08, in the opinions of Steiger (2007), Hooper et al. (2008), and Hoe (2008) [37–39]. In addition, the goodness of fit statistics (GFI) of 0.920 obtained is greater than the recommended minimum value of good fit (0.90). All other fit indices are slightly above the minimum thresholds of 0.90; CFI = 0.982; NFI = 0.966; and TLI = 0.979. Thus, all fitness measures are within the acceptable range, implying the appropriateness of the model for further analysis. As such, convergent and discriminant validities can then be tested. Using the formulas in Equations (3) and (4), and based on the descriptions of AVE, MSV, ASV, and CR, Table 7 shows the outcome of the convergent and discriminant validities.

To assess the reliability of the latent construct, CR was assessed following the minimum threshold of 0.7 by Hair et al. (2013), although Pallant (2020) suggested a value of 0.6 is acceptable [32,35]. The AVE, the square root of AVE, and MSV were computed to evaluate the validity of households' intention to separate solid waste using smart technology and its determinants. Convergent validity is deemed satisfied when CR $\geq$ 0.7 and AVE $\geq$ 0.5. Meanwhile, discriminant validity is deemed satisfied if AVE $\geq$ 0.5 and AVE > MSV, while the square root of AVE is greater than the inter-construct correlations between latent variables. Because the CR values for all latent variables are greater than

0.7 and the AVE values for all are greater than 0.5, convergent validity is deemed satisfied. This implies that the respective items for each latent variable are internally consistent and converge to the same factor. Similarly, discriminant validity is deemed satisfied for all latent variables because AVE $\geq$ 0.5 and AVE > MSV, while the square root of AVE is greater than inter-construct correlations between latent variables. Note that all bolded extreme values along the rightmost diagonal in Table 7 represent the square roots corresponding to AVE values for each latent variable, respectively. Meanwhile, all off-diagonal values under each of the AVE square roots are the inter-variable correlations between latent variables.

Table 7. Convergence and discriminant validities for household intention to separate waste and its determinants.

		CR	AVE	MSV	1	2	3	4	5	6	7
1	Attitude_Smart__Waste	0.956	0.844	0.214	**0.919**						
2	Plastic_Waste__Separation	0.678	0.535	0.179	0.198	**0.731**					
3	Daiper_Waste__Separation	0.970	0.889	0.458	0.261	0.172	**0.943**				
4	Paper_Waste__Separation	0.975	0.928	0.458	0.463	0.423	0.677	**0.963**			
5	Food_Waste__Separation	0.987	0.974	0.224	0.114	0.249	0.473	0.448	**0.987**		
6	Social__Influence	0.929	0.766	0.057	0.222	0.042	0.202	0.239	0.152	**0.875**	
7	Perceived__Behavioral__Control	0.960	0.830	0.202	0.431	0.255	0.259	0.449	0.025	0.191	**0.911**

Bolded: extreme values along the rightmost diagonal represent the square roots corresponding to AVE values for each construct, respectively.

Thus, the measurement model based on the TPB for assessing the determinants of solid waste source separation under SWMS is deemed valid. This implies that all questions or indicator variables have been empirically adjudged valid and reliable measures of the relevant latent variables. Hence, the SEM equation on the relationships between the variables can be justifiably assessed [35,36].

5. Materials and Methods

5.1. The Measurement Model

The measurement model is a sub-model that makes up the structural equation model—SEM [35]. It shows the link between latent variables and their observable indicators. The latent variables specified are either endogenous or exogenous. In the application of the TPB, shown in Figure 2, for assessing the intention or willingness to recycle solid waste through source separation using smart technology, the variables of interest include attitude towards recycling, subjective norm, perceived behavioral control, and recycling intention. The equivalent measurement model for Figure 2 specified from exploratory factor analysis (EFA) is represented as the relevant measurement model, as shown in Figure 5, using AMOS software graphics.

The measurement model in Figure 5 will be assessed for both convergent and discriminant validity as well as reliability, using confirmatory factor analysis (CFA). The equation forms of the model relating each of the indicators to respective latent variables are represented in Equations (1) and (2).

$$x_i = \Lambda_x \xi_i + \delta_i \tag{1}$$

$$y_i = \Lambda_y \eta_i + \varepsilon_i \tag{2}$$

x_i and y_i in Equations (1) and (2) correspondingly represent the matrices of indicators (measures) for exogenous and endogenous latent variables, respectively decomposable into q $\times$ 1 and $p \times 1$ vectors of observed exogenous (PBC1-PBC5, ATT1-ATT4, and SN1-SN4) and endogenous (FSEG1-FSEG4, DSEG1-DSEG4, PASEG1-PASEG5 and PSEG1-PSEG4) variables. ξi and ηi matrices are individually n $\times$ 1 and m $\times$ 1 vectors of latent exogenous (PBC, ATT, and SN) and endogenous (food, diaper, paper, and plastic waste separation) variables. Λx and Λy are, in turn, vectors of q $\times$ n and $p \times$ m factor loadings on respective latent variables, which constitute the major unknown values required for the assessment of reliability and validity. e1–e30 are q × 1 and $p \times 1$ vectors of measurement errors of x_i and y_i observed indicators. Meanwhile, $\varphi_1 - \varphi_{21}$ are measures of covariance among all latent variables.

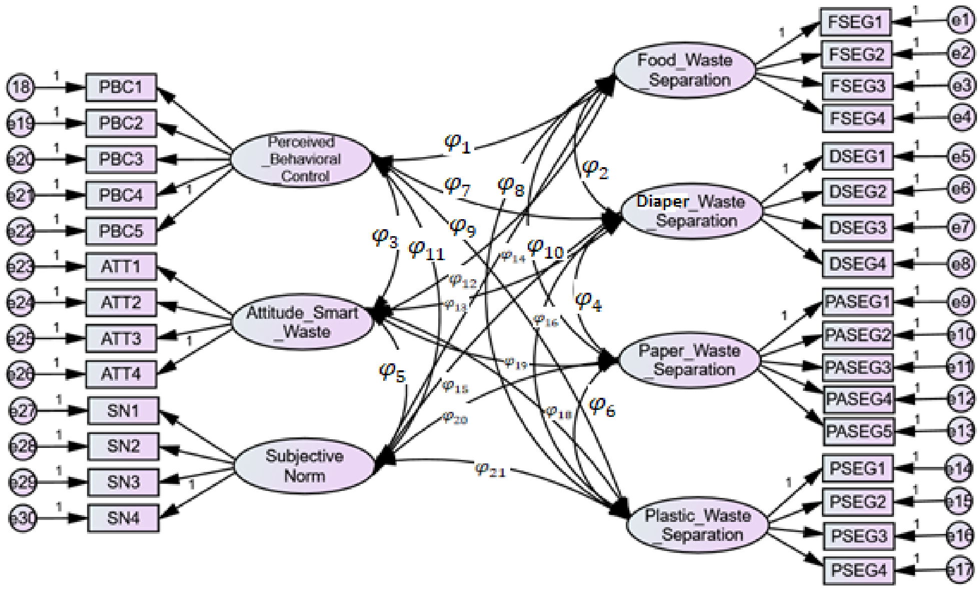

Figure 5. Measurement model for willingness to separate waste and its determinants under SWMS diaper.

Reliability and Validity of the Latent Variables

In evaluating theoretically and statistically constructed measurement models, the assessment of convergent and discriminant validities using CFA requires a few computations including the composite reliability (CR), the maximum shared squared variance (MSV), average shared squared variance (ASV) and average variance extracted (AVE) [34,36].

The CR, much like Cronbach's alpha measures, is determined using the following formula:

$$\mathrm{CR} = \frac{\left(\sum_{i=1}^{p} \lambda_i\right)^2}{\left(\sum_{i=1}^{p} \lambda_i\right)^2 + \sum_{i=1}^{p} V\ (\sigma)} \tag{3}$$

where $V\ (\sigma)$ represents the variance of the error term for the ith indicator; p represents the number of indicators; and λ_i represents standardized loading for the ith indicator. MSV is measured for each latent variable by taking the square of the highest correlation value between a latent variable and others. Meanwhile, ASV is measured for each latent variable by taking the sum of the square of all the correlation values between the latent variable and others, divided by the number of correlation values considered. The AVE is obtained by summing together the square of all standardized loadings on each latent variable, then dividing the sum by the number of indicators. Equation (4) details the formula for AVE.

$$\mathrm{AVE} = \frac{\sum_{i=1}^{p} {\lambda_i}^2}{p} \tag{4}$$

5.2. Sampling Frame, Sample Size, and Sampling Technique

In this study, the sample frame includes all households in Shah Alam. A simple random sampling procedure was adopted in a multi-stage fashion such that in the first stage, six (6) sections were randomly selected, constituting approximately 10% of the 56 sections that make up Shah Alam City. To select the 6 sections, all 56 sections were listed, while the 'Microsoft Excel® random number generator' was used to randomly select only 6 sections.

In the second stage, Google Maps was used to carefully identify major residential streets in each of the selected sections. When a selected street is deemed a commercial or business area through consultations, it would be exempted until only two streets were randomly selected from each section. The exercise yielded twelve (12) streets altogether. In the third stage, all households in the selected streets were listed, while selecting 32 households from each of the twelve streets (+1) would yield 385—the strictly required minimum number of households—following Mitchell and Carson's (1989) sampling procedure for the contingent valuation method (CVM) [40], as this research is part of a larger study, requiring the adoption of the method. Following the aforementioned procedure, the study of samples followed suggestions by Bateman et al. (2002) by randomly selecting 37 households from each street, cumulating into 444 households altogether [41]. This satisfies the minimum sample requirement for the multivariate analysis of CFA in this study because a sample size equal to or greater than 200 is considered adequate [34,36].

5.3. Questionnaire Structure and Administration

This study is part of larger research; thus, the questionnaire spans 8 pages. Data collection was conducted face-to-face from December 2021 to January 2022. The questionnaire was structured into four subsections but only the three subsections relevant to this study are reported here. The first section contains awareness and opinion questions related to traditional and smart waste management systems, including issues particular to Shah Alam. The essence of including this section is to serve as what Bateman et al. (2002) dubbed as 'warm-up' questions [41]. That is, questions were deliberately added at the beginning of the questionnaire to bring the respondents into the context of the research.

The second section contains questions on attitude and behavioral intention. This section captures questions measuring the different latent variables that constitute the TPB. These include questions on households' intention to participate in smart waste management involving source separation of waste into food waste, diaper waste, paper waste, and plastic waste. Other latent variables measured in the section include attitude, subjective norm, and perceived behavioral control. The last section of the questionnaire contains socioeconomic characteristics, including household income level, sex, educational status, and marital status, among others. The questions were added to generate information on the surveyed households.

6. Summary and Conclusions

The novel approach of SWMS has been identified as smart cities' technique potent at dealing with the myriad of problems characterizing the current traditional solid waste management. Such problems include the absence of route optimization in transporting waste, inaccessibility of real-time information exchange between the waste bin, waste generator, and waste manager, as well as the consequent increase in waste management costs. All of these elements have characterized the current traditional households' SWM, especially in Shah Alam, the capital of Selangor, which is adjudged the state with the largest waste generation in Malaysia. Although Selangor authorities have planned to introduce a robust SWMS, studies on households' willingness to support such programs remain sparse.

As such, the objective of the study is to assess Shah Alam households' intention to participate in waste source separations under the new smart waste management based on the assertions of the TPB. The outcome of the study is envisaged to guide policy and future research in understanding the dimensions of respondents' intention and its determinants. This is relevant to government advocacy. Accordingly, a theoretical measurement model following the proposition of TPB was adopted to assess the factor structure, reliability, and validity of the latent variables and their indicators (questions) using EFA and CFA.

The majority of the respondents are youthful with average age of 34.71. As many as 51.6% belong to the middle-income class, 66.7% are married, and all are educated but differ by the highest qualifications obtained. All measures of the latent variables for the TPB rated by the respondents including attitude towards source separating waste under SWMS, Subjective Norm, Perceived Behavioural Control, and Intention to sort waste into the recyclable categories were found reliable, with each having a single-factor structure, except the intention variable. The measures of the four dimensions of intention variable were based on the four policy-relevant categories of food waste, paper waste, diaper waste, and plastics. Besides being reliable, the other major factorability criteria used for evaluating the instrument include the inter-item correlation (dominance of the correlation matrix with a bivariate coefficient equal to and greater than 0.3), sample adequacy (using KMO, greater than the threshold of 0.6), communality (threshold of at least 0.3), linearity (based on Bartlet's test of sphericity, less than the 0.05 threshold). The percentage of explained variation further validated the appropriateness of the indicators as measures of the latent variables.

Finally, because EFA is not a theory-testing technique and cannot be used to assess the validity of the model, the theoretical measurement model determined based on the TPB and established factor structure from EFA was subjected to CFA for the purpose of assessing the convergent and discriminant validity of the model. The results supported the statistical convergence of all items measuring the same latent variables because convergent validity was found. In addition, the establishment of the discriminant validity also shows that no latent variable was redundant as each measured distinct variable of the TPB. Thus, to ease the uptake of the smart waste management system and solid waste separation, the government could invest in advocacy programs targeting the need to segregate waste in the four dimensions validated in this study.

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

Appendix A

Table A1. Factor analysis of willingness to separate solid waste under smart solid waste management.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0.65 [a]																
2	0.92	0.67 [a]															
3	0.47	0.51	0.78 [a]														
4	0.48	0.49	0.98	0.770 [a]													
5	0.39	0.34	0.26	0.257	0.652 [a]												
6	0.13	0.10	0.203	0.212	0.474	0.868 [a]											
7	−0.1	0.03	0.191	0.171	0.389	0.322	0.773 [a]										
8	0.37	0.33	0.262	0.253	0.967	0.445	0.368	0.692 [a]									
9	−0.01	0.02	0.616	0.609	0.448	0.314	0.273	0.444	0.881 [a]								
10	−0.20	−0.15	0.483	0.479	0.206	0.444	0.433	0.209	0.725	0.951 [a]							
11	−0.29	−0.23	0.439	0.441	0.123	0.388	0.495	0.126	0.642	0.902	0.905 [a]						
12	−0.30	−0.24	0.422	0.426	0.112	0.381	0.474	0.116	0.621	0.897	0.978	0.888 [a]					
13	−0.28	−0.22	0.428	0.413	0.118	0.381	0.475	0.121	0.624	0.888	0.957	0.96	0.925 [a]				
14	−0.08	−0.05	0.442	0.44	−0	0.199	0.344	0.222	0.416	0.592	0.656	0.664	0.66	0.932 [a]			
15	−0.08	−0.05	0.443	0.442	−0.01	0.139	0.294	−0.30	0.405	0.57	0.64	0.647	0.643	0.894	0.91 [a]		
16	−0.05	−0.03	0.431	0.428	−0.01	0.135	0.273	−0.33	0.406	0.55	0.607	0.61	0.609	0.867	0.848	0.93 [a]	
17	−0.07	−0.04	0.453	0.448	0.003	0.188	0.307	0.007	0.398	0.58	0.629	0.633	0.631	0.886	0.911	0.885	0.89 [a]
KMO (Bartlett's test of sphericity) 0.851 [b] (10849.64 ***)																	

Superscript a = measure of individual sample adequacy and b = overall measure of sample adequacy for all items, and *** denotes significance at 1%.

Table A2. Description of numbers assigned to items in the correlation matrix.

Items	Numbers in Correlation Matrix
Food leftovers	1
Organic kitchen waste	2
Domestic vegetal waste	3
Plant and flower trimmings	4
Plastic (pet) bottles	5
Used plastic utensils	6
Plastic packaging/wrapping	7
Plastic shopping bag	8
Magazines/News papers	9
Cardboards	10
Used calendars	11
Wrapping papers	12
Paper cartons	13
Disposable adult diaper	14
Disposable children diaper	15
Reusable adult diaper	16
Reusable children diaper	17

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