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Driving Consumer Adoption in Private Household Waste Collection Services: Insights from Indonesia

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ABSTRACT

Waste management that is not managed properly can have various negative impacts on ecosystems and the environment, especially the health of living things. One solution is through household waste collection services. However, there are behavioral challenges that must be overcome to achieve optimal waste management practices. This study aims to investigate the factors that affect people's intention to use household waste collection services in Indonesia. The research method used is an online survey with convenience sampling techniques, with a sample of 200 respondents. Data analysis uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to test validity, reliability, and relationships between variables. The results of the study show that environmental awareness, social norms, ease of use, and perceived value significantly affect people's intention to use household waste collection services. These findings provide valuable insights for service providers and policymakers to develop more effective strategies in driving the adoption of household waste collection services in Indonesia. The practical and theoretical implications of this study are discussed in detail.

Keywords: waste management; household waste collection; consumer adoption; behaviour;

Introduction

Mismanaged waste can cause a variety of negative effects that threaten ecosystems and the environment, especially the health of living beings. Some of them can be possible through increased risk of flooding due to blockage of drainage and sewer systems, or air pollution resulting from waste burning (UNEP, 2015). Among all types of waste, inorganic waste (plastic, metal, fabric, rubber/leather, glass, and other non-compostable materials) poses a greater risk if not handled properly because it requires a lot of time to decompose, so it will continue to accumulate in the environment until it reaches a critical point (Sidique et al., 2010).

Households are the largest source of waste in Indonesia, as shown in Figure 1. Therefore, the amount of waste generated in Indonesia is strongly influenced by household consumption or the number of residents in an area, which tends to grow as the population increases. Inorganic waste, primarily comprised of consumption waste, makes up around 39.73% of the waste generated, with plastic being the largest composition of inorganic waste. Paper/cardboard waste, which accounts for 11.1% of the waste composition, is also commonly used as packaging for consumer products, even though it is not usually considered inorganic waste. Indonesia has around 278 million people (BPS, 2023) and the number is still growing every year. With rapid population and economic growth, irresponsible production and consumption patterns with no government mitigation will result in a bigger waste management problem.

Additionally, Indonesia has not been able to balance its waste handling and reducing efforts while waste generation continues to increase. According to Indonesian Law No. 18 (2008), waste management should be a systematic, comprehensive, and sustainable activity that includes waste reduction and handling. Waste reduction includes limitation, reuse, and recycling activities, while waste handling activities include sorting, collection, transportation, processing, and final processing. Even though a strategic target of 2025 Waste-Free Indonesia consisting of 30% waste reduction and 70% waste handling has been specifically created by the law, the data presented in Figure I.3 illustrates that the Indonesian government's efforts to reduce waste have not been maximized in the past 4 years. The trend shown does not suggest that the target will be reached by 2025, which is less than one year away from now unless there are massive and rapid measurements taken. Although the percentage of managed waste has been increasing every year, the percentage of mismanaged waste has not decreased. Moreover, the National Plastic Action Partnership (2020) reported that a significant portion of plastic waste is not managed properly.

The government has admitted in the 2020-2024 National Medium-Term Development Plan (RPJMN) that low implementation of waste reduction principles and limited waste reduction infrastructure, such as Integrated Waste Management Sites (Tempat Pengolahan Sampah Terpadu, TPST) and Reuse, Reduce, Recycle Waste Management Sites (Tempat Pengolahan Sampah, TPS 3R), are the reasons of waste household mismanagement. Access to waste management in urban areas only covers 61% of households. On the other hand, waste transportation efforts in urban areas are challenged by the lack of transportation fleets and geographical challenges.

That said, Indonesia is currently facing a critical issue of waste management. There needs to be more than the prevailing approach of managing waste downstream, and it is vital to involve society as waste producers in managing their waste responsibly. However, there are persistent behavioral challenges that should be addressed to pursue optimal waste management practices.

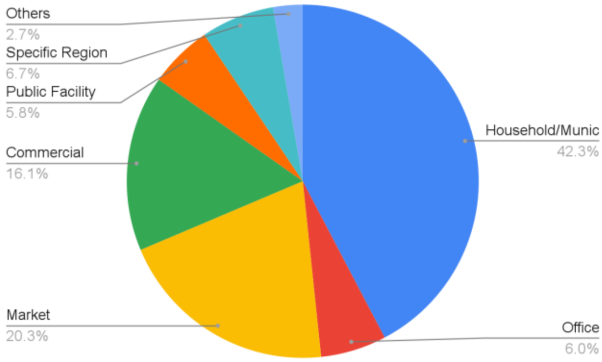

Figure 1
Amount of Waste Generated in Indonesia Based on Source in 2023
(Ministry of Environment and Forestry, 2023)

Behavioral aspects have a significant impact on waste management. They influence how individuals produce waste, make disposal decisions, and engage in recycling. Waste management behavioral challenges in Indonesia stem from various factors. (Al-Sulami et al., 2017) explain the lack of awareness, unavailability of clear guidelines, and the limited capacity of the current recycling sector as concerns and issues of fulfilling producer responsibility in waste management. These factors are furthermore related to each other as several factors, such as perceived practicality and convenience in the context of consumption, lack of knowledge on how to implement alternatives or lack of opportunity, strong habits, and shifting responsibilities, are found to override awareness in regards to responsible consumption behavior change (Heidbreder et al., 2019). Ali et al. (2023) also highlight the socio-economic aspect, which further divides local communities' lack of awareness and commitment. The 'green attitude-behavior gap' is prevalent, where attitudes towards sustainability do not always translate into sustainable purchasing actions related to waste management services (Khatun et al., 2024). When trying to adopt a more sustainable lifestyle, Indonesian consumers have expressed concerns such as the high cost of sustainable products, skepticism towards brands and manufacturers, time constraints, lack of facilities, and availability, among others (FMCG Gurus, 2021).

Method

Research Design

A research design specifies a framework or blueprint that lays the foundation for conducting the marketing research project. Figure 2 represents the research design of this study.

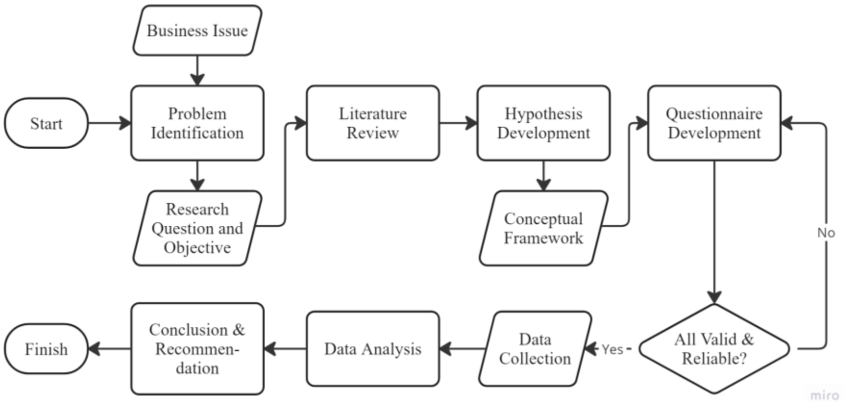

Figure 2
Research Design

Data Collection Method

To gather information on individuals' intentions to use household waste collection services, this study will employ an online survey.

Population and Sampling Technique

In this research, convenience sampling, a non-probability sampling technique, will be employed as individuals are conveniently available to provide the data. The sampling size is following the recommendation of (Malhotra, 2020), which is 200 people.

Questionnaire Design

The questionnaire for this research study was developed based on the hypotheses established and the conceptual research conducted in the previous chapter. It encompasses 11 variables and 48 measuring items.

Measurement Model Analysis

A pilot test will be conducted to examine the questionnaire's validity and reliability. In this pilot test, the questionnaire will be administered to a sample of 40 respondents.

Reliability Test

In survey research, internal consistency reliability is commonly assessed using Cronbach's alpha, a statistical measure particularly suitable for evaluating items with multiple response options, such as those on a Likert scale (Sulastri & Jufri, 2021). Additionally, composite reliability accounts for the varying outer weights of indicator variables, aligning closely with the priorities of PLS-SEM, which emphasizes the importance of indicators. Both Cronbach's alpha and composite reliability produce values ranging from 0 to 1.00, with values above 0.7 being deemed satisfactory (Mondal & Hasan, 2023).

Validity Test

According to (Malhotra, 2020), validity refers to how well the observed scale scores reflect actual differences among objects based on the characteristic being measured, rather than being influenced by random or systematic errors. In this research, construct validity will be evaluated to assess the operationalization of a construct (Taherdoost, 2016). Construct validity includes both convergent and discriminant validity. Convergent validity ensures that items intended to measure the same construct are highly correlated.

Data Analysis Method

Partial Least Squares Structural Equation Modeling (PLS-SEM)

Structural equation modeling (SEM) is a modeling technique to estimate complex relationships among multiple dependent and independent variables (Hair et al., 2017). This research will specifically use partial least squares SEM (PLS-SEM) which can explain the variance in the dependent variable. In SEM, hypotheses are represented in path models. The variables in these models are categorized into two types: latent variables and manifest variables.

Collinearity

Collinearity, also known as multicollinearity, occurs when there are high correlations between two or more formative indicators. This issue can be assessed by calculating the Variance Inflation Factor (VIF). A VIF value exceeding 5 suggests that one of the corresponding indicators should be removed to ensure the reliability of the analysis.

Explanatory and Predictive Power

Explanatory power in a PLS path model refers to the model's ability to fit the data by quantifying the strength of the relationships between variables, typically measured by the coefficient of determination (R^2). In contrast, predictive power assesses the model's ability to accurately forecast future observations, often evaluated using Stone-Geisser’s Q^2 statistic (Hair et al., 2021). A model is considered to have predictive relevance if the Q^2 value is greater than 0, indicating that it can reliably predict future data points.

Effect Size

The f^2 effect size is a measure used to assess the relative impact of a predictor construct on an endogenous construct in terms of its explanatory power. It is directly related to the R^2 value, as it represents the change in R^2 when a specific predictor construct is removed from the model. In the context of moderating effect analysis, the f^2 effect size indicates the extent to which the moderator contributes to the explanation of the endogenous construct. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 correspond to weak, moderate, and strong effects, respectively.

Ethics

Ethics play a crucial role in the research process, ensuring integrity and respect for participants. (Howard et al., 2018) emphasize that ethical responsibility in research involves safeguarding the dignity of participants and maintaining the accuracy and honesty of research findings. To uphold these principles, the researcher provides informed consent, detailing the confidentiality and privacy measures in place for participant data, which will be used solely for academic purposes. By completing the questionnaire, respondents acknowledge they have read and agreed to these terms, thereby providing their informed consent.

Results and Discussion

Reliability Test Analysis

First, data reliability analysis is performed by evaluating the reliability of the indicators. Since all indicators have an outer loading greater than 0.708, it can be concluded that the indicators used in this questionnaire are reliable. The results of the indicator reliability testing are presented in Table 1.

Table 1
Indicator Reliability Test Result

Variable	Item Label	Outer Loading	Reliability
Performance Expectancy	PE1	0.738	Reliable
	PE2	0.836	Reliable
	PE3	0.773	Reliable
Effort Expectancy	EE1	0.794	Reliable
	EE2	0.861	Reliable
	EE3	0.871	Reliable
	EE4	0.776	Reliable
Social Influence	SI1	0.898	Reliable
	SI2	0.882	Reliable
	SI3	0.874	Reliable
	SI4	0.908	Reliable
Facilitating Conditions	FC1	0.897	Reliable
	FC2	0.857	Reliable
	FC3	0.774	Reliable
Hedonic Motivation	HM1	0.909	Reliable
	HM2	0.925	Reliable
	HM3	0.915	Reliable
Price Value	PV1	0.799	Reliable
	PV2	0.715	Reliable
	PV3	0.801	Reliable
	PV4	0.836	Reliable
	PV5	0.756	Reliable
Incentives	IN1	0.905	Reliable
	IN2	0.911	Reliable
	IN3	0.918	Reliable

	IN4	0.882	Reliable
Drop-Off	CM1	0.921	Reliable
	CM2	0.888	Reliable
	CM3	0.932	Reliable
Pick-Up	CM4	0.859	Reliable
	CM5	0.886	Reliable
	CM6	0.856	Reliable
Behavioral Intention	BI1	0.907	Reliable
	BI2	0.909	Reliable
	BI3	0.897	Reliable

Subsequently, internal consistency reliability is assessed using Cronbach's alpha and composite reliability values, as presented in Table 2. Out of the ten variables, only Performance Expectancy is considered quite reliable, as its Cronbach’s alpha value falls below 0.7, which is still within an acceptable range. However, this will be taken into account in the next stage of testing the measurement model.

Table 2
Internal Consistency Reliability Test Result

Variable	Cronbach's Alpha	Composite Reliability	Reliability
Performance Expectancy	0.684	0.826	Acceptable
Effort Expectancy	0.845	0.896	Reliable
Social Influence	0.913	0.939	Reliable
Facilitating Conditions	0.797	0.881	Reliable
Hedonic Motivation	0.904	0.94	Reliable
Price Value	0.844	0.887	Reliable
Incentives	0.926	0.947	Reliable
Drop-Off	0.901	0.938	Reliable
Pick-Up	0.835	0.901	Reliable
Behavioral Intention	0.888	0.931	Reliable

Validity Test Result

Table 3 presents the results of the construct validity test, evaluated through the average variance extracted (AVE) values. Each variable exhibits an AVE value greater than 0.5, indicating that all constructs meet the criteria for construct validity. This demonstrates that the variables adequately capture the underlying constructs they are intended to measure.

Table 3
Construct Validity Test Result

Variable	Average Variance Extracted (AVE)	Validity
Performance Expectancy	0.613	Valid
Effort Expectancy	0.683	Valid
Social Influence	0.793	Valid
Facilitating Conditions	0.712	Valid
Hedonic Motivation	0.839	Valid
Price Value	0.612	Valid
Incentives	0.818	Valid
Drop-Off	0.835	Valid
Pick-Up	0.752	Valid
Behavioral Intention	0.817	Valid

The discriminant validity test is evaluated using the Heterotrait-Monotrait (HTMT) ratio. The results, displayed in Table 4, reveal that only the Performance Expectancy construct has two values exceeding 0.85, indicating a potential issue with its discriminant validity. To address this, Hair et al. (2022) recommend enhancing the average monotrait-heteromethod correlations by removing indicators with low correlations to other items measuring the same construct. Consequently, the indicator PE3 ("Using private household waste collection service increases my productivity") is removed. This adjustment leads to an improvement in discriminant validity, as evidenced by the updated results in Table 5.

The final reliability and validity assessment is summarized in Table IV.7. Performance Expectancy has a Cronbach's alpha value below 0.7, which will later be eliminated from the model because of the lack of internal consistency reliability. All other constructs exhibit Cronbach's alpha values above 0.7, indicating good internal consistency. Furthermore, the composite reliability and AVE values for all variables confirm that each construct has satisfactory internal consistency reliability, and convergent validity.

Table 4
Discriminant Validity Test Result (Former)

	BI	DO	EE	EE * DO	EE * PU	FC	FC * DO	FC * PU	HM	Inc	PE	PU	PV	PV * DO	PV * PU	SI
BI																
DO	0.516															
EE	0.848	0.567														
EE * DO	0.454	0.156	0.501													
EE * PU	0.493	0.136	0.496	0.409												

FC	0.734	0.609	0.833	0.186	0.356										
FC * DO	0.277	0.216	0.178	0.369	0.378	0.377									
FC * PU	0.478	0.122	0.398	0.453	0.696	0.37	0.342								
HM	0.746	0.465	0.789	0.423	0.375	0.672	0.187	0.403							
Inc	0.37	0.404	0.333	0.105	0.188	0.4	0.215	0.122	0.34						
PE	0.875	0.61	0.949	0.388	0.5	0.803	0.264	0.408	0.762	0.359					
PU	0.655	0.431	0.663	0.153	0.477	0.662	0.12	0.453	0.596	0.379	0.76				
PV	0.755	0.647	0.772	0.296	0.296	0.833	0.296	0.36	0.758	0.538	0.781	0.763			
PV * DO	0.333	0.259	0.293	0.566	0.287	0.321	0.689	0.309	0.345	0.265	0.286	0.191	0.422		
PV * PU	0.433	0.177	0.328	0.305	0.628	0.363	0.267	0.722	0.376	0.216	0.425	0.581	0.472	0.392	
SI	0.53	0.524	0.653	0.158	0.303	0.665	0.142	0.255	0.675	0.352	0.691	0.684	0.661	0.175	0.385

Table 5
Discriminant Validity Test Result (Latter)

	BI	DO	EE	EE * DO	EE * PU	FC	FC * DO	FC * PU	HM	Inc	PE	PU	PV	PV * DO	PV * PU	SI
BI																
DO	0.516															
EE	0.848	0.567														
EE * DO	0.454	0.156	0.501													
EE * PU	0.493	0.136	0.496	0.409												
FC	0.734	0.609	0.833	0.186	0.356											
FC * DO	0.277	0.216	0.178	0.369	0.378	0.377										
FC * PU	0.478	0.122	0.398	0.453	0.696	0.37	0.342									
HM	0.746	0.465	0.789	0.423	0.375	0.672	0.187	0.403								
Inc	0.37	0.404	0.333	0.105	0.188	0.4	0.215	0.122	0.34							
PE	0.81	0.50	0.84	0.40	0.49	0.66	0.18	0.41	0.72	0.26						

	4	8	7	1	5	1	9	9	3	2					
PU	0.655	0.431	0.663	0.153	0.477	0.662	0.12	0.453	0.596	0.379	0.683				
PV	0.755	0.647	0.772	0.296	0.296	0.833	0.296	0.36	0.758	0.538	0.695	0.763			
PV * DO	0.333	0.259	0.293	0.566	0.287	0.321	0.689	0.31	0.345	0.265	0.23	0.191	0.422		
PV * PU	0.433	0.177	0.328	0.305	0.628	0.363	0.267	0.722	0.376	0.216	0.421	0.581	0.472	0.392	
SI	0.53	0.524	0.653	0.158	0.303	0.665	0.142	0.255	0.675	0.352	0.561	0.684	0.661	0.175	0.385

Table 6
Reliability and Validity Test Result After Indicator Removal

Variables	Internal Consistency Reliability			Construct Validity	
	Cronbach's Alpha	Composite Reliability	Reliability	Average Variance Extracted (AVE)	Validity
Performance Expectancy	0.639	0.846	Not Reliable	0.733	Valid
Effort Expectancy	0.845	0.896	Reliable	0.683	Valid
Social Influence	0.913	0.939	Reliable	0.793	Valid
Facilitating Conditions	0.797	0.881	Reliable	0.712	Valid
Hedonic Motivation	0.904	0.94	Reliable	0.839	Valid
Price Value	0.844	0.887	Reliable	0.612	Valid
Incentives	0.926	0.947	Reliable	0.818	Valid
Drop-Off	0.901	0.938	Reliable	0.835	Valid
Pick-Up	0.835	0.901	Reliable	0.752	Valid
Behavioral Intention	0.888	0.931	Reliable	0.817	Valid

Structural Model Analysis

Following the initial assessment of the measurement model, this section will analyze the structural model with the SmartPLS software. The model includes the latent variables: Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Incentives, Drop-Off, Pick-Up, and Behavioral Intention.

Collinearity

The results of the multicollinearity assessment are presented in Table IV.8. Multicollinearity is assessed using the Variance Inflation Factor (VIF). According to the assessment results, all indicators meet the criteria by having VIF values below 5, indicating that there is no close correlation between two or more formative indicators.

Table 7
Collinearity Assessment Result

Indicator	VIF	Indicator	VIF
EE1	1.822	PV3	3.038
EE2	2.202	PV4	2.576
EE3	2.305	PV5	2.19
EE4	1.596	IN1	3.68
SI1	2.922	IN2	3.567
SI2	2.642	IN3	3.912
SI3	2.773	IN4	2.773
SI4	3.265	CM1	3.25
FC1	2.171	CM2	2.401
FC2	1.856	CM3	3.221
FC3	1.502	CM4	1.953
HM1	2.877	CM5	2.221
HM2	3.007	CM6	1.793
HM3	2.835	BI1	2.658
PV1	2.833	BI2	2.646
PV2	1.934	BI3	2.434

Explanatory and Predictive Power

The assessment of explanatory and predictive power includes the coefficient of determination (R^2) and predictive relevance (Stone-Geisser's Q^2). Table 8 presents the R^2 and Q^2 values of the Price Value and Behavioral Intention variables.

Table 8
Explanatory and Predictive Power Assessment Result

Variable	R^2	Q^2
Price Value	0.261	0.14
Behavioral Intention	0.661	0.509

The R^2 value, or coefficient of determination, indicates the proportion of variance in the dependent variable that is explained by the independent variables in the model. For Price Value, the R^2 value is 0.261, meaning that 26.1% of the variance in Price Value is explained by the independent variables. This suggests a moderate level of explanatory power for the model about Price Value. In contrast, the R^2 value for Behavioral Intention is 0.661. This indicates that 66.1% of the variance in Behavioral Intention is explained by the independent variables, reflecting a high level of explanatory power. Therefore, the model is quite effective in explaining the variance in Behavioral Intention.

The Q^2 value, obtained through a blindfolding procedure, evaluates the predictive relevance of the model, offering insights into its predictive accuracy. For latent variables, the Q^2 value for Price Value is 0.14 while for Behavioral Intention, it is 0.509. Since both values are greater than 0, the model demonstrates predictive power. However, when analyzing the manifest variables, the Q^2 value for PV3 was found to be negative, indicating low predictive power. This prompted further examination of the manifest variable and its associated latent variable, Price Value. Upon removing the PV3 indicator, an issue arose with the factor loading of another indicator, PV2. As a result, the decision was made to modify the model by eliminating the function of Price Value as a potential mediator between Incentives and Price Value. With this change, the model fit criterion is met, which will be discussed in the next sub-subchapter, ensuring the integrity of the measurement model as well as the structural and formative models. Consequently, the analysis will proceed without including the mediating effect of the Price Value variable.

Table 9
Explanatory and Predictive Power Assessment Result After Model Change

Variable	R^2	Q^2
Behavioral Intention	0.662	0.509

f^2 Effect Size

The f-squared effect size assessment provides insights into the relative impact of various predictor variables on Behavioral Intention (BI). Effort Expectancy (EE) exhibits a weak effect on Behavioral Intention, with an f^2 value of 0.07, indicating that it has a modest yet noticeable influence on users' intention to engage with household waste collection services. Similarly, Hedonic Motivation (HM) also shows a weak effect, with an f^2 value of 0.049, suggesting that the pleasure or enjoyment derived from using the service plays a minor role in shaping Behavioral Intention.

In contrast, other variables, such as Social Influence (SI), Facilitating Conditions (FC), Price Value (PV), and Incentives, display f^2 values ranging from 0.002 to 0.019, indicating that these factors do not have a significant effect on Behavioral Intention within this model. This suggests that, in this context, elements like social pressures, resource availability, perceived value, and incentives are not major drivers of users' intention to use the service.

The analysis also examines the moderating effects of Drop-Off (DO) and Pick-Up (PU) models in combination with Effort Expectancy, Facilitating Conditions, and Price Value. The results show no significant moderating impact, as indicated by the low f^2 values (ranging from 0.0 to 0.01) for these interactions. This implies that the presence of these collection models does not meaningfully alter the relationships between the primary predictors and Behavioral Intention.

Overall, the f-squared effect size assessment highlights that while Effort Expectancy and Hedonic Motivation have some influence on Behavioral Intention, other factors, including the examined moderating effects, do not significantly contribute to explaining users' intentions within the model.

Table 10
f^2 Effect Size Assessment Result

Variable	f^2	Effect Size
EE → BI	0.07	Weak

SI → BI	0.019	No effect
FC → BI	0.014	No effect
HM → BI	0.049	Weak
PV → BI	0.012	No effect
Incentives → BI	0.002	No effect
EE * DO → BI	0.01	No effect
FC * DO → BI	0	No effect
PV * DO → BI	0.002	No effect
EE * PU → BI	0.006	No effect
FC * PU → BI	0.005	No effect
PV * PU → BI	0.007	No effect

Model Fit

The goodness of fit for this model is evaluated using the Root Mean Square Error (RMSE). Table IV.11 presents the RMSE results for the manifest variables, calculated through PLSpredict in SmartPLS. When compared to the corresponding linear regression model values, the RMSE obtained from the PLS-SEM analysis is lower for all assessed manifest variables of Behavioral Intention. This indicates that the model possesses strong predictive power.

Table 11
Root Mean Square Error Assessment Result

Indicator	RMSE PLS	RMSE LV	Lower Prediction Error
BI1	0.453	0.479	RMSE PLS
BI2	0.399	0.521	RMSE PLS
BI3	0.428	0.437	RMSE PLS

Path Coefficients

The significance and relevance of the path coefficients are analyzed using the bootstrapping method, which allows for the calculation of empirical t-values and p-values for all structural path coefficients (Hair et al., 2022). The analysis was conducted using 5,000 resamples as per Hair et al. (2011) recommendation. Figure IV.13 illustrates the model employed in the bootstrapping process, which comprises 9 latent variables and 32 indicators, with 2 variables serving as moderators in 2 of the relationships.

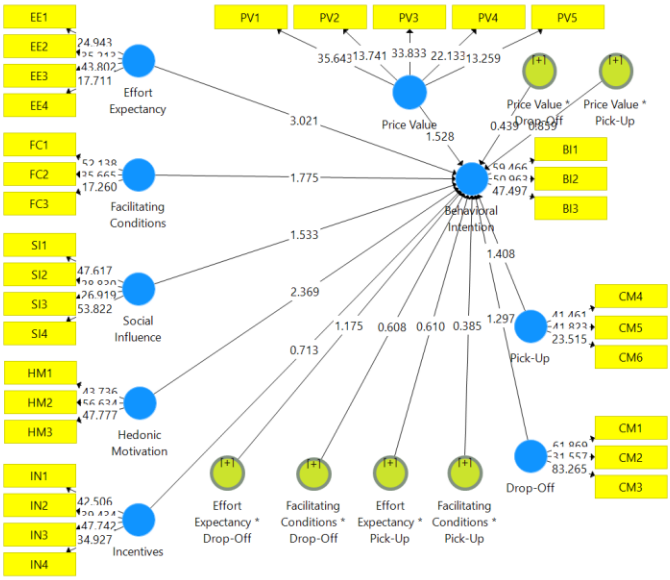

Figure 3
Graphical Output of Bootstrapping Procedure

Table 3 presents the bootstrapping results using a two-tailed test with a 5% significance level. In this context, the null hypothesis is rejected if the p-value is less than 0.05, indicating that the observed effect is statistically significant and unlikely to have occurred by chance. Additionally, a t-value greater than 1.96 in a two-tailed test at this significance level typically denotes statistical significance, reinforcing the reliability of the relationship between variables in the model.

Table 12
Bootstrapping Results and Hypothesis Testing

Hypothesis		Path Coefficient (β)	Standard Deviation	t-value	p-value	Result
H2	EE → BI	0.301	0.1	3.021	0.003	Accepted
H3	SI → BI	-0.126	0.082	1.533	0.125	Rejected
H4	FC → BI	0.117	0.066	1.775	0.076	Rejected
H5	HM → BI	0.219	0.093	2.369	0.018	Accepted
H6	PV → BI	0.12	0.079	1.528	0.127	Rejected
H7b	Incentives → BI	0.033	0.047	0.713	0.476	Rejected
H8a	EE * DO → BI	-0.105	0.089	1.175	0.24	Rejected
H8b	FC * DO → BI	-0.043	0.071	0.608	0.543	Rejected
H8c	PV * DO → BI	-0.039	0.089	0.439	0.661	Rejected
H8d	EE * PU → BI	-0.045	0.073	0.61	0.542	Rejected
H8e	FC * PU → BI	-0.035	0.091	0.385	0.7	Rejected
H8f	PV * PU →	0.08	0.094	0.859	0.39	Rejected

BI

The results indicate that Effort Expectancy (EE) has a significant positive effect on Behavioral Intention (BI), with a path coefficient of 0.301, a t-value of 3.021, and a p-value of 0.003. This supports the hypothesis H2 that Effort Expectancy is a key driver of Behavioral Intention. Similarly, Hedonic Motivation (HM) also significantly influences Behavioral Intention, as indicated by a path coefficient of 0.219, a t-value of 2.369, and a p-value of 0.018, confirming hypothesis H5.

In contrast, several other variables do not show a significant effect on Behavioral Intention. Social Influence (SI), Facilitating Conditions (FC), and Price Value (PV) have p-values of 0.125, 0.076, and 0.127 respectively, leading to the rejection of hypotheses H3, H4, and H6. These results suggest that social pressures, the availability of resources, and perceived value for money do not significantly impact the intention to use household waste collection services in this model. Additionally, the hypothesis testing for Incentives (H7b) shows no significant effect on Behavioral Intention, with a p-value of 0.476, indicating that offering incentives may not be effective in this context.

The results also demonstrate that the moderating effects of the collection models (Drop-Off and Pick-Up) on the relationships between the key predictors and Behavioral Intention are not significant. All the interaction terms (H8a to H8f) have p-values greater than 0.05, leading to the rejection of these hypotheses. This suggests that the moderating role of the collection models does not significantly alter the impact of the primary predictors on Behavioral Intention.

The Effect of Effort Expectancy on Behavioral Intention

The hypothesis test confirms that H2 is accepted, indicating that effort expectancy has a positive and significant effect on behavioral intention. This finding is consistent with the research of Godinho Filho et al. (2024), which also highlight the importance of convenience and ease of use in influencing behavior. This suggests that individuals place a high value on the simplicity and effortlessness of household waste collection services. Ironically, this reflects a common mindset among many Indonesians, who often view waste disposal as merely the act of getting rid of waste, without considering the broader implications for sustainability and the long-term impact of waste processing.

Interestingly, the analysis shows differing results based on the collection models used: individuals who have exclusively used either the drop-off or pick-up models accepted the null hypothesis, indicating that effort expectancy significantly influences their experience. However, those who have utilized both collection models rejected the null hypothesis. This indicates that individuals who have tried both models may not see ease of use as a decisive factor in their overall experience with household waste collection services. Since these users have tried each of the collection models, which vary in levels of ease and convenience, they may no longer base their decision to use the service on expectations of ease of use. This indicates that consumers familiar with both models may not see ease of use as a decisive factor in their overall experience with household waste collection services.

The Effect of Social Influence on Behavioral Intention

The analysis shows that the effect of social influence on behavioral intention to use household waste collection services is insignificant, leading to the rejection of hypothesis H3. This finding contrasts with the research by (Cioc et al., 2023) on energy efficiency smart solutions, suggesting that the impact of social influence may vary across different types of green services. This discrepancy implies that individuals do not consider the influence of family, neighbors, important people, and broader social networks to be a significant factor in their decision to use household waste collection services. This result correlates with the research of (Moltene & Orsato, 2021) which states that social influence is not so relevant for food waste reduction platforms.

The Effect of Facilitating Condition on Behavioral Intention

The analysis reveals that facilitating conditions generally have an insignificant effect on behavioral intention to use household waste collection services, leading to the rejection of hypothesis H4. This finding contrasts with the research by Venkatesh et al. (2012) and Farida et al. (2024), which identified a significant impact of facilitating conditions on behavioral intention, particularly in the context of household waste collection services. One possible explanation for this discrepancy could be the lack of exposure to recycling and related practices among certain user groups. When individuals have limited experience or familiarity with recycling processes, they may not fully recognize or value the importance of having the necessary resources, knowledge, and support when deciding to use these services.

However, the analysis shows that facilitating conditions are significant for individuals who have used both collection models. This suggests that those familiar with both models are more likely to consider the resources, knowledge, and access to support they have when using these services. On the other hand, this effect is insignificant for individuals who have only used one model, possibly due to their more limited and less varied experience with the service. Therefore, while hypothesis H4 is rejected overall, there is evidence that facilitating conditions may play a role in influencing behavioral intention among users with broader experience, particularly those who have been exposed to multiple collection models and are more attuned to the practical aspects of recycling.

The Effect of Hedonic Motivation on Behavioral Intention

The analysis confirms the acceptance of hypothesis H5, indicating that hedonic motivation has a generally positive and significant effect on behavioral intention to use household waste collection services. This finding aligns with the research by Rezvani et al. (2018), which observed a similar phenomenon in the context of green products. The results suggest that the positive emotions associated with using these services can significantly influence the intention to continue using them. This finding is particularly intriguing in light of Choi & Johnson's (2019) research, which highlights that the novelty-seeking aspect of hedonic motivation can positively impact an individual's decision to purchase green products. It would be worthwhile to explore whether the same novelty-seeking tendencies might also drive the use of household waste collection services, as this could further explain the role of hedonic motivation in this context. Notably, this hypothesis is accepted by users of both collection models, whereas it is rejected by users of either model alone. This contrast suggests that the broader experience of using both models may enhance the role of hedonic motivation in shaping behavioral intention.

The Effect of Price Value on Behavioral Intention

The analysis reveals that hypothesis H6 is rejected, indicating that price value has no significant effect on the intention to use household waste collection services overall. This suggests that, in general, individuals do not prioritize the monetary cost of the service when considering its benefits. Interestingly, this finding does not align with the research by (Moltene & Orsato, 2021), both of which state that price value significantly affects behavioral intention in the usage of green products. However, the multi-group analysis reveals an interesting exception: the group of people who have specifically used drop-off services shows a positive relationship between price value and usage intention, suggesting that these users do consider the monetary value of the service. It is noteworthy that drop-off services typically do not require payments, which might contribute to the significance of price value for this group. Meanwhile, other user groups do not support this relationship, highlighting a potential difference in how price value is perceived depending on the specific service model used.

The Effect of Incentives on Behavioral Intention

In this research, incentives are found to have an insignificant effect on behavioral intention to use household waste collection services, leading to the rejection of hypothesis H7b. This suggests that incentives play a less critical role in influencing individuals' decisions to use these services. Interestingly, this finding contrasts with Thøgersen's (2003) research, which demonstrated that incentives have a positive and significant impact on environmental behaviors. However, the result is consistent with (Bertagnolio et al., 2024), who also found that financial incentives are insignificant in shaping individual intention to use waste management services. The study suggests that this rejection may be attributed to a misinterpretation of the financial concept and individuals' lack of knowledge regarding incentives. Specifically, the misinterpretation arises because the incentives might have not been directly linked to the price value of waste management services but rather introduced as potential costs or rewards for waste separation. This could lead to confusion or a lack of clarity among individuals, diminishing the perceived relevance of these incentives in their decision-making process.

The Effect of Collection Models

The bootstrapping results indicate that the moderating effect of collection models is insignificant, leading to the rejection of hypotheses H8a through H8f. This means that collection models do not significantly moderate the relationships between effort expectancy, facilitating conditions, and price value on behavioral intention to use household waste collection services, despite the inherent differences between the models. One possible reason for this rejection could be the limited knowledge and exposure to recycling practices among individuals. When users lack familiarity with the specific processes and benefits associated with different collection models, they may be less likely to consider how these models could impact their behavior or intentions. Additionally, it is possible that the perceived convenience or effectiveness of these models is not distinct enough to influence users' decisions significantly. This lack of differentiation between collection models might also contribute to the rejection of the moderating effect. However, it is worth noting that several hypotheses are supported within specific user groups, suggesting that moderating effects may still exist for certain variables under particular conditions. These findings imply that while the overall moderating effect of collection models is not significant, there may be nuanced influences at play that warrant further investigation.

Conclusion

This research aims to explore the challenges associated with the behavioral implementation of recycling in Indonesia, particularly through the efforts of household waste collection services, and to propose business solutions that promote their use. By employing the PLS-SEM method, this study provides a comprehensive understanding of the factors influencing recycling behavior and offers actionable insights. The following sections summarize the key findings and recommendations derived from the research.

RQ1: What are the factors influencing the intention to use household waste collection services and their significance?

The study concludes that the intention to use household waste collection services is positively and significantly influenced by individuals' effort expectancy and hedonic motivation. Additionally, facilitating conditions show a significant impact on users of both collection models, while price value significantly influences only drop-off users. On the other hand, social influence and incentives do not demonstrate a significant relationship with the behavioral intention to use these services. Overall, these findings highlight the importance of convenience, enjoyment, and certain contextual factors in shaping users' intentions to engage with household waste collection services.

RQ2: What can be suggested for the household waste collection industry in Indonesia in improving their business to reinforce responsible consumption and create a sustainable recycling behavior? To improve the household waste collection industry in Indonesia and promote sustainable recycling behavior, service providers should tailor their services to different user segments based on their characteristics. Service providers should also focus on creating user-friendly services that enhance convenience and make waste management enjoyable. Additionally, improving facilitating conditions—such as offering flexible service schedules, expanding mobile collection units, and strategically placing drop-off points—will increase accessibility. Finally, combining these efforts with public education campaigns and strict regulation enforcement will reinforce responsible consumption and support long-term sustainability goals.

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