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Behavioral Determinants of Environmental Health Impacts in IoT-Enabled Waste Management: Evidence from Greater Jakarta Urban Households

E. Ernyasih[1]*, N. Nelfiyanti[2], Eka Samsul Ma'arif[3], Aulia Fahreza Ismanto[3], Donita Lutfia Hasanah[1], D. Daruki[4]
[1]Faculty of Public Health, Universitas Muhammadiyah Jakarta, 15445 Jakarta Indonesia
[2]Department of Industrial Engineering, Faculty of Engineering, Universitas Muhammadiyah Jakarta, 10510 Jakarta, Indonesia
[3]Department of Electrical Engineering, Faculty of Engineering, Universitas Muhammadiyah Jakarta, 10510 Jakarta, Indonesia
[4]Department of Industrial Engineering, Faculty of Engineering, Universitas Mercu Buana, Jakarta, Indonesia

***Corresponding Author:** Email: ernyasih@umj.ac.id

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ABSTRACT

Introduction: The rapid growth of household waste in urban areas poses a serious challenge to environmental health. The integration of the IoT into waste management is considered an innovative solution, offering real-time monitoring, collection efficiency, and greater system transparency. This study aims to examine the influence of perception, attitude, awareness, and practices on environmental health impacts in the context of IoT adoption.
Methods: A cross-sectional survey was conducted with 120 households in the Greater Jakarta area, and the data were analyzed using SEM-PLS.
Results: The results reveal that perception significantly influences attitude ($p < 0.001$), and attitude significantly influences awareness ($p < 0.001$). The structural model demonstrates strong predictive power with R^2 values of 0.566 for attitude, 0.552 for awareness, and 0.839 for environmental health impacts. Standardized path coefficients show significant effects for perception → attitude ($\beta = 0.752$; $p < 0.001$), attitude → awareness ($\beta = 0.743$; $p < 0.001$), and practices → environmental health impact ($\beta = 0.864$; $p < 0.001$). Model diagnostics confirm reliability and validity, including AVE > 0.50, CR > 0.70, HTMT < 0.85, and VIF < 3. However, awareness does not directly affect environmental health ($p > 0.05$), indicating the presence of an intention–behavior gap. In contrast, actual waste management practices emerged as the most dominant predictor, with the largest effect on environmental health outcomes ($p < 0.001$).
Conclusion: These findings highlight the necessity of policy strategies that go beyond raising awareness and digital literacy, ensuring the transformation of awareness into consistent practices through adequate infrastructure, incentive systems, and regulatory enforcement. This study contributes to strengthening the concept of smart cities and supports sustainable development strategies in urban settings.

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INTRODUCTION

Urbanization has significantly increased the amount of household waste generated, posing a major challenge to environmental health. The World Bank estimates that global waste production will increase from 2.01 billion tons in 2016 to 3.40 billion tons in 2050, with Asia being the largest contributor (1–3). Waste management is a series of integrated processes that include collection, storage, processing, transportation, final disposal, and recycling. All stages are designed with a systematic approach to minimize potential harm to human health, the survival of fauna, ecological stability, and overall environmental quality (4). Suboptimal waste management can trigger air and water pollution, while increasing the risk of environment-based diseases (5–7) through vectors such as mosquitoes (8,9) and rats(10,11) and indirectly affecting climate change (12,13).

The development of Internet of Things (IoT) technology has revolutionized urban waste management through the integration of sensors, digital applications, and data analytics. The implementation of smart bins with volume sensors, GPS-based tracking systems, and route optimization algorithms allows for increased efficiency, lower operational costs, and reduced carbon emissions from waste transportation (14–16). IoT also aligns with the sustainable development agenda by supporting recycling, strengthening city government accountability, and increasing the transparency of waste management systems (17).

IoT integration aligns with the smart city development agenda through its role in reducing carbon emissions, increasing governance transparency, and encouraging active community participation(18,19). This alignment is reflected in a study conducted by Vishnu (2021) in West Lafayette, United States, who designed an IoT system to monitor waste volume in real time as part of a smart city initiative (20).

From a behavioral perspective, public perception, attitude, and awareness are key factors in the successful adoption of IoT-based waste management systems. Perceptions of the usefulness and ease of technology influence attitudes, which in turn strengthen awareness of environmental health consequences (21–23). Strong awareness can encourage sustainable behavior that positively impacts environmental health (24,25). Furthermore, practical household waste management practices also directly contribute to improved sanitation quality and reduced disease risk (26,27).

Recent evidence further demonstrates that behavioral patterns in waste handling are strongly associated with measurable public health outcomes. For instance, household sorting behavior is linked to reductions in vector density, particularly mosquitoes and rodents, which are known mediators of dengue, leptospirosis, and typhoid transmission. Studies in developing metropolitan areas show that improved waste practices significantly correlate with decreases in water contamination, better air quality, and lower sanitation-related morbidity indexes (28,29). These empirical findings reinforce the public-health relevance of behavioral determinants in waste governance.

Previous research has tended to focus on technical-operational aspects, while the socio-behavioral dimensions of households as daily waste users and managers have received less attention. This research gap underlies the importance of a behavioral approach in the context of smart waste management. The purpose of this study is to analyze and model the variables of residents' perceptions, attitudes, awareness, and practices in IoT-based household waste management and to assess their implications for urban environmental health.

METHOD

This study design uses a cross-sectional approach with a quantitative approach to examine the causal relationship between household behavioral constructs in waste management and their implications for urban environmental health in the context of IoT adoption. The target population is households in the urban areas of Jakarta, Depok, Tangerang, and Bekasi in July 2025. These areas were selected because they face complex problems in waste management. Participants were recruited through community networks, neighborhood associations, and household clusters registered under municipal waste programs. Eligibility screening ensured that respondents were adults (≥18 years old), permanent residents, and responsible for household waste management. Households without direct involvement in waste handling or temporary residents were excluded. A sample of 120 respondents was selected using purposive sampling with the criteria of respondents being at least 18 years old, living in urban areas, and having involvement in household waste management.

The research variables are X1: waste management practices, namely the frequency and quality of sorting, recycling, utilization of waste banks, compliance with schedules/facilities, and the use of IoT solutions; X2: perceptions of IoT related to perceived usefulness, convenience, reliability, affordability; X3: attitudes towards IoT, namely affective-cognitive evaluations of the application of IoT in waste management, X4: environmental awareness, namely knowledge and sensitivity to the environmental-health consequences of waste and the benefits of sustainable practices, and Y: environmental health impacts, namely perceptions of the quality of residential environments related to cleanliness, disease vectors, and sanitation.

All constructs were measured using validated scale items adapted from previous TPB, VBN, and IoT adoption studies. Each latent variable consisted of 4–6 reflective indicators on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Content validity was ensured through expert review, while reliability and convergent validity were confirmed through PLS-SEM measurement testing (CA > 0.70; CR > 0.70; AVE > 0.50).

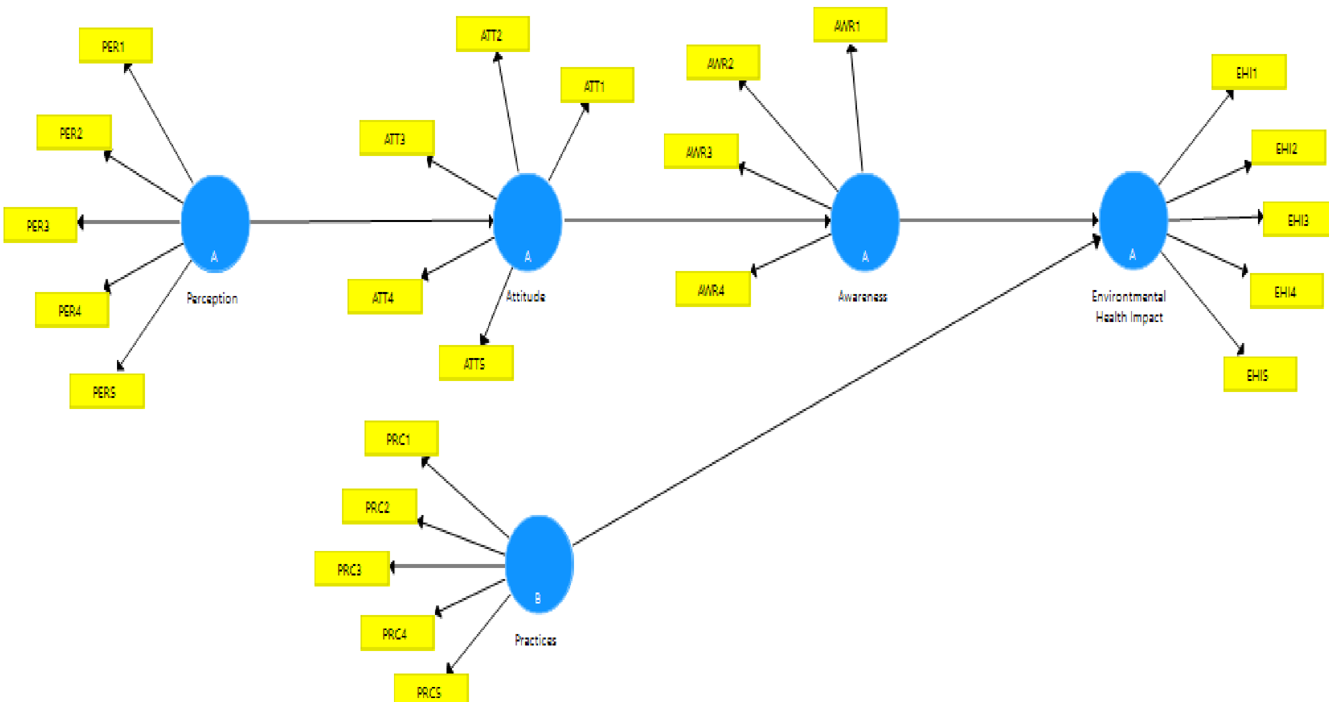

Figure 1. Conceptual Model of Behavioral Determinants and Environmental Health Impacts in IoT-Based Waste Management

The theoretical framework of this research is based on the Theory of Planned Behavior (TPB), which emphasizes the role of perception and attitude in shaping intention and behavior, and the Value-Belief-Norm (VBN) Theory21, which asserts that values and moral awareness act as mediators in sustainable behavior. The integration of these two theories provides a strong conceptual foundation for understanding IoT adoption in the context of smart waste management with the following hypotheses: H1: Household perception of IoT-based waste management (X2) has a positive effect on household attitude (X3). H2: Household attitude (X3) has a positive effect on household awareness (X4). H3: Household awareness (X4) has a positive effect on environmental health impacts (Y). H4: Household waste management practices (X1) have a positive effect on environmental health impacts (Y). H5: Household attitude (X3) mediates the relationship between household perception (X2) and household awareness (X4). H6: Household awareness (X4) mediates the relationship between household attitude (X3) and environmental health impacts (Y). H7: Household attitudes (X3) and household awareness (X4) sequentially mediate the relationship between household perceptions (X2) and environmental health impacts (Y).

Data analysis in this study was conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS). This approach was chosen because it can test predictive models with latent variables that have both reflective and formative indicators, and is suitable for relatively limited sample sizes. The analysis stages include outer model testing and inner model testing.

Ethics Approval and Consent to Participate

Ethical approval was granted under certificate number 10.235.C/KEPK-FKMUMJ/V/2025. All participants provided informed consent, and confidentiality was strictly maintained throughout data collection.

RESULTS

The results of the descriptive analysis show that all variables have an average value above 4.00, which indicates a tendency for respondents to be in the positive to very positive category in table 1. Household waste management practices (X1) are at a high level with an average of 4.50; SD = 0.61, reflecting residents' consistency in sorting, recycling, and compliance with regulations as part of their daily routine. Conversely, perceptions of IoT technology (X2) are the weakest dimension with an average of 3.14; SD = 0.68, indicating doubts among some respondents regarding the benefits, convenience, and reliability of the technology and indicating a gap in awareness in the acceptance of innovation. However, household attitudes (X3) towards environmentally friendly practices are recorded as positive with an average of 4.34; SD = 0.66, in line with the level of awareness (X4) which is also high with an average of 4.35; SD = 0.65 towards the health risks and ecological impacts of waste. Assessment of environmental health impacts (Y) shows a relatively good condition with an average of 4.43; SD = 0.70, indicating an environment perceived as clean and at low risk for waste-related diseases. Overall, this profile affirms strong behavioral readiness and pro-environmental norms, but highlights barriers in the technology perception dimension. Intervention strategies that close the perception gap, for example through digital literacy, performance demonstration, provision of measurable evidence of benefits, and regulatory support, are needed to increase IoT adoption in waste management alongside established good practices.

Table 1. Overview of Behavioral Determinants and Environmental Health Impacts of IoT-Based Waste Management in Urban Households

Variable	Mean	SD
Perception (X2)	3.14	0.68
Attitude (X3)	4.34	0.66
Awareness (X4)	4.35	0.65
Practices (X1)	4.50	0.61
Environmental Health Impact (Y)	4.43	0.70

Reliability and construct validity test

The results of the measurement model evaluation in Table 2 show that all latent constructs exceed the criteria for internal reliability and convergent validity with Cronbach's Alpha (CA) ≥ 0.70 and Composite Reliability (CR) ≥ 0.70, with Average Variance Extracted (AVE) > 0.50 for each construct. Specifically, the Environmental Health Impact (Y) construct recorded the highest metrics (CA = 0.941; CR = 0.955; AVE = 0.811), which confirms the strong representation power of the indicators towards the conceptual domain and the consistency of respondents' perceptions on this dimension.

Table 2. Results of Reliability and Construct Validity Tests

Variable	Cronbach's Alpha	rho_A	Composite Reliability (CR)	AVE
Attitude (X3)	0.879	0.886	0.912	0.675
Awareness (X4)	0.853	0.871	0.901	0.695
Environmental Health Impact (Y)	0.941	0.944	0.955	0.811
Perception (X2)	0.857	0.870	0.897	0.636
Practices (X1)	0.908	0.951	0.928	0.721

The discriminant test based on the Fornell–Larcker criterion in Table 3 shows that the square root of the AVE located on the diagonal of the correlation matrix is greater than the correlation between constructs in the corresponding column. The Attitude construct obtained √AVE = 0.822 which exceeds its correlation with

Awareness (r = 0.743), Environmental Health Impact (r = 0.684), Perception (r = 0.752), and Practices (r = 0.716). A similar pattern was found for all other constructs, so that each construct shared a greater variance with its own indicators compared to other constructs. These results indicate that the discriminant validity of the measurement model was met.

To further confirm discriminant validity, the HTMT ratios were calculated, with all constructs recording HTMT values ranging from 0.421 to 0.811, remaining below the recommended threshold of 0.85. Multicollinearity assessment also showed that all VIF values were below 3, indicating no collinearity issues among predictors

Table 3. Discriminant Validity Test

Variable	Attitude	Awareness	Environmental Health Impact	Perception	Practices
Attitude	0.822				
Awareness	0.743	0.834			
Environmental Health Impact	0.684	0.744	0.901		
Perception	0.752	0.799	0.894	0.797	
Practices	0.716	0.786	0.915	0.896	0.849

Correlation Analysis

The Pearson correlation test results in Table 4 indicate that all variables have a strong to very strong positive relationship ($r > 0.70$). Perception of IoT is closely correlated with attitude (r = 0.752), while attitude is strongly related to awareness (r = 0.743). Awareness is also correlated with environmental health impacts (r = 0.744), although the strongest contribution is shown by actual waste management practices (r = 0.915) to health impacts. The high correlation between perception, practice, and environmental health (r = 0.894–0.896) indicates that positive perceptions and actual behavior play a complementary role in creating a clean and healthy environment. Overall, these results support the proposed structural model, namely the perception → attitude → awareness → health impacts pathway, with practice as the primary determinant of environmental quality.

Table 4. Pearson Correlation Test Results

Variable	Attitude (X3)	Awareness (X4)	Environmental Health Impact (Y)	Perception (X2)	Practices (X1)
Attitude (X3)	1.000	0.743	0.684	0.752	0.716
Awareness (X4)	0.743	1.000	0.744	0.799	0.786
Environmental Health Impact (Y)	0.684	0.744	1.000	0.894	0.915
Perception (X2)	0.752	0.799	0.894	1.000	0.896
Practices (X1)	0.716	0.786	0.915	0.896	1.000

Structural analysis (SEM-PLS)

In Structural Equation Modeling based on Partial Least Squares (SEM-PLS), internal model analysis focuses on testing the structural relationships between constructs and measuring the extent to which independent variables are able to contribute to explaining the dependent variable. Evaluation at this stage is generally carried out through two main indicators, namely the Coefficient of Determination (R^2) which represents the predictive power of the model, and the Effect Size (F^2) which is used to assess the magnitude of the influence of independent variables on the dependent variable in a structural context.

Coefficient of determination (R2)

Table 5 displays the model's explanatory capacity for each endogenous construct through the coefficient of determination (R^2) and adjusted R^2. In general, all R^2 values are at a moderate to very strong level, with a very small difference between R^2 and adjusted R^2 (0.002–0.004). This minimal difference indicates a parsimonious model, stable against degrees of freedom corrections, and at low risk of overfitting. Attitude (X3) has an $R^2 = 0.566$ (adjusted $R^2 = 0.562$), indicating that 56.6% of the variance in attitude is explained by Perception (X2). Furthermore, Awareness (X4) recorded an $R^2 = 0.552$ (adjusted $R^2 = 0.548$), meaning that 55.2% of the variance in awareness is influenced by Attitude (X3). Meanwhile, Environmental Health Impact (Y) reached $R^2 = 0.839$ (R^2 adjusted = 0.837), indicating that 83.9% of the variance in environmental health outcomes was explained jointly by Awareness (X4) and especially Practices (X1).

This consistent pattern indicates that actual practices are the primary driver of outcomes, while the direct path from awareness to Y is insignificant, thus strengthening the conclusion that changes in environmental health conditions are more determined by actual behavior than by increased awareness alone. On the other hand, the "moderate" level of explanation for attitude and awareness opens up room for model enrichment (e.g., by adding subjective norms, self-efficacy, or policy support) to strengthen the cognitive-affective trajectory towards behavior and impact. Overall, the obtained goodness of fit confirms the explanatory adequacy of the structural model for inference purposes and policy implications in the context of technology-based waste management.

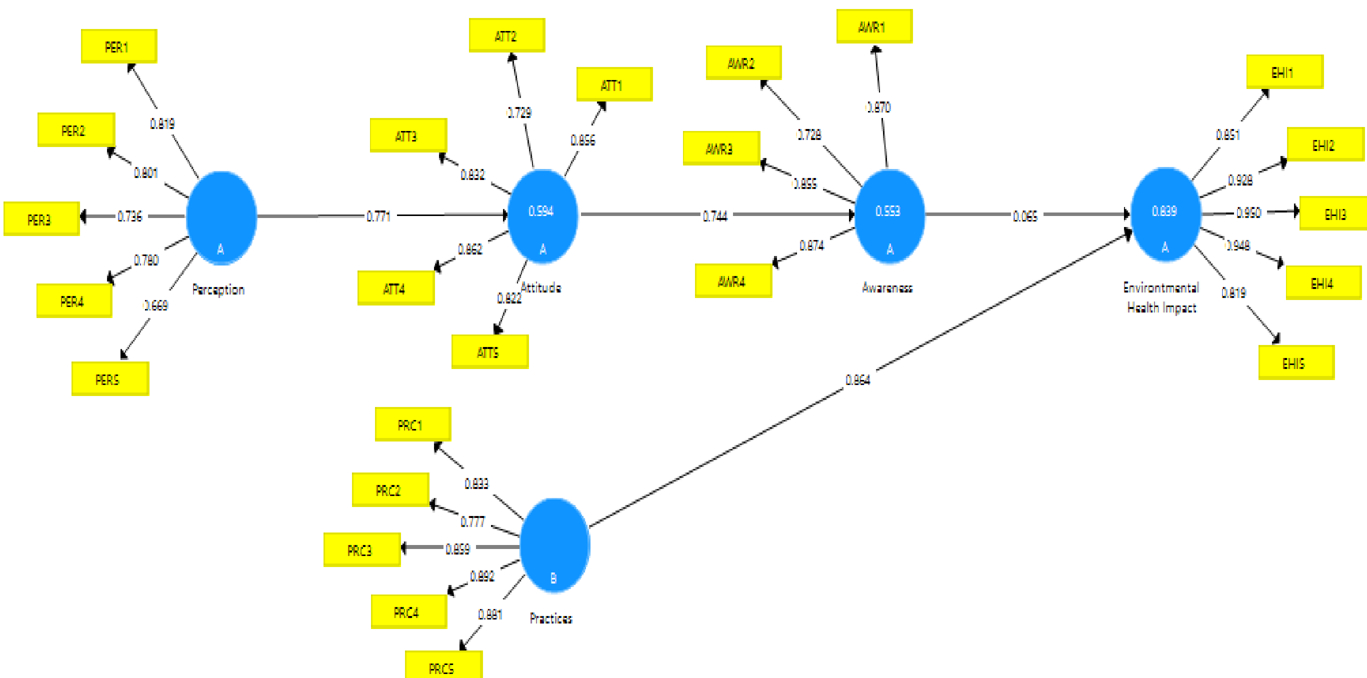

Figure 2. Structural Model Results of SEM-PLS Analysis (Standardized Path Coefficients)

Table 5. R-Square Test Results

Dependent Variable	R^2	R^2 Adjusted
Attitude (X3)	0.566	0.562
Awareness (X4)	0.552	0.548
Environmental Health Impact (Y)	0.839	0.837

Table 6 presents the effect size f^2 for each path in the SEM-PLS structural model. Conceptually, f^2 quantifies the unique contribution of a predictor to the increase in the coefficient of determination (R^2) of the endogenous construct, namely the difference between the R^2 of the full model and the R^2 after the predictor is removed, normalized by $1 - R^2$ of the full model. Referring to convention, values exceeding 1.00 indicate a very substantive effect.

Table 6. Results of f2 values

Relationship Between Variables	f^2
Perception → Attitude	1.302
Attitude → Awareness	1.233
Awareness → Environmental Health Impact	0.010
Practices → Environmental Health Impact	1.778

The results show that Perception → Attitude ($f^2 = 1.302$) and Attitude → Awareness ($f^2 = 1.233$) have very large effect sizes, confirming the role of perception as a lever for attitude formation and, subsequently, attitude as a strong antecedent to awareness. The Practices → Environmental Health Impact pathway obtained the largest effect size ($f^2 = 1.778$), indicating that waste management practices are the dominant determinant of environmental health outcomes. In contrast, Awareness → Environmental Health Impact had an $f^2 = 0.010$ (negligible), consistent with the insignificance of this pathway in the significance test, making its contribution to the variance of the outcomes practically insubstantial.

Table 7 summarizes the structural path testing using the bootstrapping procedure. With a significance criterion of $p < 0.05$, it was found that H1 was accepted: Perception (X2) → Attitude (X3) had a positive and significant effect ($\beta = 0.752$; $t = 13.427$; $p = 0.000$), confirming that a more positive perception is associated with a more supportive attitude. H2 was also accepted: Attitude (X3) → Awareness (X4) had a significant positive effect ($\beta = 0.743$; $t = 14.336$; $p = 0.000$), indicating that pro-environmental attitudes encourage increased awareness. Conversely, H3 was rejected: the direct effect of Awareness (X4) → Environmental Health Impact (Y) was not significant ($\beta = 0.065$; $t = 1.257$; $p = 0.209$), so that increased awareness alone does not necessarily affect environmental health outcomes. In line with that, H7 is accepted and becomes the strongest path: Practices (X1) → Y is significantly positive ($\beta = 0.864$; $t = 18.710$; $p = 0.000$), confirming the dominance of actual practices in determining environmental health conditions.

Table 7. Hypothesis test results

Relationship Between Variables	Coefficient (β)	t-statistic	p-value	Decision
Perception (X2) → Attitude (X3)	0.752	13.427	0.000	Accepted
Attitude (X3) → Awareness (X4)	0.743	14.336	0.000	Accepted
Awareness (X4) → Environmental Health Impact (Y)	0.065	1.257	0.209	Rejected
Perception (X2) → Attitude (X3) → Awareness (X4)	–	–	0.001	Accepted
Attitude (X3) → Awareness (X4) → Environmental Health Impact (Y)	–	–	0.001	Rejected
Perception (X2) → Attitude (X3) → Awareness (X4) → Environmental Health Impact (Y)	–	–	0.001	Rejected
Practices (X1) → Environmental Health Impact (Y)	0.864	18.710	0.000	Accepted

Mediation tests revealed a pattern consistent with the cognitive–affective chain. H4 was accepted (partial mediation): Attitude (X3) mediates the effect of Perception (X2) on Awareness (X4) (significant indirect, p 0.001), but the remaining direct effect remained significant, thus being partial. H5 was rejected (indirect Attitude → Awareness → Y was not significant) because the X4 → Y link was not supported. Similarly, H6 was rejected: the serial mediation of Perception → Attitude → Awareness → Y was not met because the final segment leading to Y was not significant.

These results confirm that changes in environmental health outcomes are primarily driven by concrete management practices, while raising awareness without supporting behavioral changes is insufficient to generate impact. These results are consistent with the upstream-downstream framework, where perceptions shape attitudes, attitudes foster awareness, and practices are the ultimate determinants of environmental health impact.

DISCUSSION

The results of this study confirm that IoT-based household waste management practices play a dominant role in determining the impact on urban environmental health. This finding is consistent with recent literature showing that concrete behavioral interventions, such as sorting, recycling, and the use of waste management technology, have a more direct impact on sanitation quality than simply raising awareness or educational campaigns(30–32). This aligns with the theory of planned behavior (TPB), which emphasizes that intention and awareness are only effective when translated into concrete actions(33,34). These results reinforce the awareness–practice gap widely reported in sustainability literature, where cognitive understanding does not automatically translate into concrete behavioral action without structural support. Given the cross-sectional nature of this study, causal interpretations should be made cautiously; the results indicate associations rather than definitive causal pathways. Moreover, socio-technical constraints—such as uneven digital literacy, limited access to IoT infrastructure, and disparities in neighborhood-level service delivery—may further influence the behavioral translation into environmental-health outcomes

Perception and attitude as initial determinants

The results of this study confirm that the Perception → Attitude path is one of the most significant relationships in the model. SEM-PLS analysis shows that Perception → Attitude has $\beta = 0.752$; $t = 13.427$; $p < 0.001$ with an effect size of $f^2 = 1.302$, indicating a very strong contribution in explaining the variance in attitudes ($R^2 = 0.566$). This means that more than half of the variation in residents' attitudes towards IoT-based waste management is explained by their perceptions of the benefits, convenience, reliability, and affordability of the technology.

This finding is consistent with the VBN and TPB frameworks, which emphasize that perceived usefulness and perceived ease of use are important antecedents in forming positive attitudes toward technology adoption. In the context of this study, respondents with positive perceptions of IoT were more likely to develop pro-environmental attitudes that support the implementation of smart waste management systems (35) .

Recent literature supports these findings. Nassani et al. (2023) found that perceived usefulness of environmentally friendly technologies was significantly associated with pro-adoption attitudes in urban households (36). Similarly, Hin et al. (2021) confirmed that the ease of use of IoT systems such as smart bins increased people's positive attitudes toward sustainable consumption practice (37). Research by Liang et al. (2024) also showed that perceived reliability and safety of technology were important predictors that strengthened positive attitudes toward environmentally friendly behavior (38).

On the other hand, the descriptive findings of this study indicate that perception is the construct with the lowest average value (Mean = 3.14; SD = 0.68) compared to attitude (Mean = 4.34; SD = 0.66) and awareness (Mean = 4.35; SD = 0.65). This indicates a perception gap, despite the general positive attitude of residents. This condition aligns with the study by Gade et al. (2021), which found that public acceptance of environmental technology is often hampered by low digital literacy and a lack of concrete evidence of the technology's benefits (39).

Intervention strategies that close the perception gap so that the cognitive-affective pathway can function optimally are building digital literacy through public campaigns and community-based education, providing measurable evidence of IoT performance, for example real-time reports from smart bins regarding waste volume or transportation efficiency and ensuring the reliability and affordability of the technology, so that residents feel the direct benefits of IoT adoption.

The role of environmental awareness

The results of this study indicate that household attitudes significantly influence awareness ($\beta = 0.743$; $t = 14.336$; $p < 0.001$; $f^2 = 1.233$), but awareness does not have a significant direct effect on environmental health impacts ($\beta = 0.065$; $t = 1.257$; $p = 0.209$; $f^2 = 0.010$). Thus, although pro-environmental attitudes have succeeded in increasing the level of public awareness, this awareness has not yet been converted into a tangible impact on environmental health quality. This phenomenon demonstrates the existence of an "intention–behavior gap," namely the gap between intention/awareness and actual behavior, which is also reported in various sustainability studies (40).

Conceptually, these results emphasize that environmental awareness is a cognitive-affective factor between attitudes and practices, but it does not necessarily drive changes in environmental health conditions if it is not transformed into concrete behavior. Geiger et al. (2019) emphasized that sustainability awareness is only effective when supported by structural and social support, such as the availability of sorting facilities, participation incentives, and social norms that encourage environmentally friendly behavior. This is consistent with the conditions of this study, where waste management practices proved to be far more dominant in determining environmental health quality than awareness alone (41).

Recent literature confirms that awareness tends to act as a weak mediator if not supported by public policy. Ulhasanah et al. (2025) show that the implementation of incentive-based policies, such as the digital waste bank program, can bridge the gap between awareness and concrete action at the household level (42). Suhardono et al. (2025) also highlight that the adoption of digital technology only successfully improves environmental outcomes when communities are not only aware but also facilitated with easily accessible tools and strong regulatory support (43).

The practical implication of this research is that raising awareness alone is not enough to drive environmental change. Environmental education programs need to be combined with regulatory instruments (e.g., mandatory waste sorting, administrative sanctions for violations), incentive schemes (financial or non-financial rewards through digital waste banks), infrastructure support (availability of smart bins, easily accessible recycling facilities), and strengthening social norms to ensure public awareness gains broader community suppor.

Practice as the main determinant

The results of this study indicate that actual household waste management practices are the strongest determinant of urban environmental health. SEM-PLS analysis shows that the Practices → Environmental Health Impact path is significant with $\beta = 0.864$; $t = 18.710$; $p < 0.001$ and an effect size of $f^2 = 1.778$, making it the largest influence in the model. This confirms that the success of waste management is not driven by increased awareness or attitudes alone, but is highly dependent on concrete behavior and consistency of daily practices.

These findings align with recent literature highlighting the direct impact of household practices on reducing waste generation and the risk of environmental-based diseases. Zhang et al. (2024) confirmed that sorting and recycling practices can reduce waste generation by up to 30%, while simultaneously reducing the burden on landfills (44). Research by Anokye et al. (2023) also demonstrated that consistent waste sorting at the household level can reduce the risk of vector-based diseases in urban areas (45). Similarly, Yue et al. (2025) found that sorting-based interventions significantly contributed to reducing the prevalence of environmental diseases (46).

The results of this study also show an intention–behavior gap, namely the gap between awareness and actual practice. The Awareness → Environmental Health Impact pathway proved insignificant ($\beta = 0.065$; $p = 0.209$), indicating that increased awareness does not automatically result in environmental health impacts without being translated into actual practice. This condition is consistent with the findings of Syed et al. (2024) who emphasized that the gap between intention and behavior is a major challenge in encouraging sustainable consumption and practices (35).

From a policy perspective, these results emphasize the need to shift focus from simply increasing knowledge or awareness to empowering citizen practices. Sembiring et al. (2024) showed that the success of waste management in Indonesia is heavily influenced by a combination of practice-based education, regulatory support, and participation incentives(3). Research by Hussain et al. (2024) also confirmed that smart city initiatives that integrate IoT with citizen behavior through smart bins and digital applications successfully reduce waste generation and carbon emissions (47).

Thus, the results of this study enrich the literature with empirical evidence that real-world practices are the primary pathway that determines the quality of environmental health. Perception, attitude, and awareness remain important as cognitive-affective foundations, but real impact is only achieved when residents implement consistent and sustainable waste management practices. Therefore, IoT-based urban waste management programs should emphasize the provision of supporting infrastructure for practices (sorting facilities, smart bins, digital waste banks), the implementation of incentive and disincentive schemes to encourage consistent behavior, and digital data-based monitoring to ensure sustainable and measurable practices.

CONCLUSION

IoT-based household waste management has significant implications for urban environmental health, with each behavioral determinant playing a distinct role. First, perception has been shown to be a key cognitive foundation in shaping attitudes. Respondents with positive perceptions of the benefits, convenience, reliability, and affordability of IoT demonstrated a more supportive attitude toward the implementation of this technology. Furthermore, attitudes play a role in increasing environmental awareness, although the direct path from awareness to environmental health impacts is insignificant. This confirms the existence of the intention-behavior gap, where awareness does not necessarily translate into real change without the support of infrastructure, regulations, and public policy instruments.

Second, actual waste management practices are a dominant determinant of environmental health quality. This finding is consistent with recent literature confirming that concrete behaviors such as sorting, recycling, and the use of digital systems and waste banks contribute directly to waste reduction and the risk of environmentally-related diseases. With the largest effect sizes, practices are the primary pathway for ensuring the sustainability of the positive impacts of technological interventions.

The practical implications of this research are the need for policy strategies that not only emphasize increasing literacy and awareness, but also ensure the conversion of awareness into real practices through the provision of adequate sorting infrastructure, the implementation of consistent incentives and disincentives, and the use of digital technology to monitor citizen participation. Conceptually, these results strengthen the integration of the SDGs and VBN frameworks, with perception as the initial lever, attitude as the affective mediator, awareness as the cognitive catalyst, and practice as the main determinant that produces a real impact on environmental health quality. Thus, this research not only provides an empirical contribution to the study of sustainable behavior in the context of smart cities, but also offers a conceptual and practical basis for the formulation of more effective, participatory, and sustainable IoT-based urban waste management policies.

In the context of Greater Jakarta, these findings highlight the need for municipalities to integrate IoT-enabled waste programs with behavioral incentives, ensure equitable access to sorting facilities, and deploy neighborhood-based digital monitoring systems. Policy levers such as mandatory household sorting, reward-based waste bank applications, and data-driven vector-control interventions could significantly enhance the environmental health benefits of IoT governance.

In metropolitan settings such as Greater Jakarta, effective environmental health improvements will require the alignment of resident practices with digital infrastructure readiness, including reliable smart-bin networks, municipal incentives, and transparent data-sharing systems. This creates a synergistic pathway between behavioral engagement and technological governance

AUTHOR’S CONTRIBUTION STATEMENT

E. as Conceptualization; Methodology; Writing - original draft; Supervision; Validation, N as formal analysis; Project administration; Resources), E as Project administration; Resources; Investigation, AL as Validation; Investigation, DL as Writing - review & editing; Data curation, D as formal analysis.

CONFLICTS OF INTEREST

The authors declare there is no conflict of interest.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

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