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An Analysis on The Effect of Perceived Vulnerability and Benefit on E-Waste Management Practices

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ABSTRACT
The issue of electronic waste is becoming increasingly problematic in both advanced and emerging nations due to the presence of harmful substances in nearly all electronic waste items, which can have negative effects on human health and the environment. The objective of the study was to examine the influence of perceived vulnerability and benefit on e-waste management practices among electronic technicians.In this study, we utilized the Health Believe Model to determine how perceived vulnerability and benefits influence the e-waste management practices of electronic technicians. The study was carried out using a cross-sectional survey approach and the sample was obtained by employing proportionate stratified random sampling methodology. Out of the 265 questionnaire that were administered, 248 were completed and returned.Statistical procedures were employed to address the issues associated with missing data, outliers, and normality. Consequently, unidimensionality was established by conducting principal component analysis with varimax rotation. Partial Least Square Structural Equation Modelling (PLS-SEM) version 3.2.6 was used to evaluate the research model. The results of hypothesis testing indicated a significant impact of Perceived Benefit on e-waste management practice. The study successfully introduced a novel approach that combines various potential factors influencing e-waste management practices. Consequently, enhancing the understanding and perception of the benefits associated with e-waste can lead to improvements in e-waste management practices among electronic technicians. The findings of this study will provide valuable support to decision-makers in formulating policies that promote effective e-waste management practices, not only among electronic technicians but also among all users of information technology.

Keywords: E-waste; E-waste Management Practice; Perceived Vulnerability; Perceived Benefit.

1. Introduction

The emergence of the knowledge economy has placed significant pressure on developing nations to adopt digital technologies to integrate into the global community (Maphosa & Maphosa, 2020). The rapid pace of modernization, industrialization, and increasing consumer demand for improved products has intensified the challenges associated with e-waste management. The lifespan of computers and peripherals has significantly decreased from the previous range of 5-10 years to the current range of 3-4 years. This shift is attributed to the fact that the design is focused on replacement rather than repair, as stated by Agamuthu et al., (2015). Due to these circumstances, e-waste is emerging as the fastest growing waste stream in the industrialized world (Chaturvedi et al., 2011).

E-waste comprises valuable as well as hazardous materials that necessitate specific handling and recycling techniques to prevent environmental contamination and mitigate potential adverse impacts on human health (Robinson, 2009). The improper dismantling and recycling of e-waste in impoverished and developing nations pose significant risks to both human health and the environment(Laissaoui & Rochat, 2008). e-waste contains a range of hazardous substances, including lead, mercury, beryllium, cadmium, and brominated flame-retardants, among others, as well as valuable materials such as iron, aluminium, nickel, copper, gold, silver, platinum-group metals (platinum, palladium, rhodium, ruthenium, iridium, osmium)(Ogungbuyi et al., 2012).This makes e-waste a critical concern.When e-waste becomes irreparable, it is often discarded, posing significant hazards to the environment, wildlife, and human beings. This e-waste is associated with a wide array of toxic chemicals or toxicants.

A notable factor contributing to the rapid accumulation of e-waste in Africa is the prevalence of electronic devices that have second-hand value and reach their half-life shortly after being imported, rendering them obsolete (Orisakwe et al., 2020).

Africa has been identified as a destination for the disposal of toxic chemicals and e-waste from developed nations, with estimates suggesting that up to 80% of the world's high-tech waste finds its way to Asia and Africa(Ewuim *et al.*, 2014). The soils surrounding an informal e-waste recycling site in Nigeria have shown increased levels of various heavy metals, including copper, lead, zinc, manganese, nickel, antimony, chromium, and cadmium (Lebbie et al., 2021).

Even though e-waste poses inherent dangers, it has been noticed that electronic technicians who handle and accumulate such waste often display a lack of awareness and understanding regarding its hazardous nature. Similarly, there is a lack of available literature on the influence of perceived vulnerabilities and benefits on e-waste management practices in developing nations, specifically among electronic technicians.Building upon the aforementioned gaps in the literature, the study investigated the factors that determine e-waste management practices among electronic technicians.

2. Literature Review

The term "electronic and electrical waste" (e-waste) encompasses electrical or electronic equipment that is considered waste, including all its components, subassemblies, and consumables that are part of the equipment at the point when it becomes waste (Lebbie et al., 2021). A more technical definition of e-waste would describe it as obsolete or discarded products whose primary functions are facilitated by electronic circuitry and components(Sivakumar et al., 2012).

Since 2010, there has been a consistent and significant increase in the global volume of e-waste generated. By 2019, the total e-waste produced reached approximately 53.6 million metric tons, representing a substantial increase of 44.4 million metric tons in just five years. Alarmingly, only 17.4 percent of this e-waste was documented to be collected and subjected to proper recycling processes (Wang, 2019). This trend can be attributed to several factors, such as increasing consumer demand for electronic products, high rates of obsolescence, short innovation cycles, and low recycling rates (Bimir, 2020). According to Ogungbuyi *et al.*, (2012), around 30% of second-hand imports into Nigeria were considered to be non-functioning. Out of this portion, half of the non-functioning items were repaired locally and sold to consumers, while the other half was deemed unrepairable.

E-waste management encompasses a series of activities aimed at the safe collection, transportation, segregation, dismantling, reduction, reuse, and repair of electronic waste in an environmentally friendly manner(Sivakumar et al., 2012). E-waste management is primarily undertaken to minimize the adverse effects of electronic waste on human health and the environment. Additionally, it aims to recover valuable resources from e-waste through recycling and proper disposal practices.

In general, e-waste management involves implementing strategies that align with the 4R principle: Reduce, Recover, Reuse, and Recycle. These strategies aim to minimize the overall amount of waste generated while maximizing resource recovery.

Importation of e-waste

The importation of e-waste into developing nations generate employment opportunities and provide a supply of second-hand products for reuse within those countries.In several African countries, the recycling and dismantling of electronic devices have emerged as significant sources of employment and income. This informal sector often involves individuals and communities engaging in e-waste recycling activities to extract valuable materials and components for resale or reuse (Lebbie et al., 2021).Although some governments have implemented bans on the export of e-waste to developing nations, the practice continues to increase due to economic incentives associated with informal recycling(Namias, 2013). The improper dumping and recycling of e-waste in various African countries have significant implications, as it serves as a major source for the release of harmful substances. This improper handling and disposal contribute to environmental pollution and pose risks to both human health and ecosystems (Lebbie et al., 2021).

Health implication of e-waste

E-waste is a global issue that mostly affect developing countries due to the many toxic and hazardous materials that are sources of environmental pollution, contamination of groundwater and surface water, thus harmful to human health (Terada, 2012). E-waste comprises various substances that can pose significant health risks to both humans and the environment if they are released or disposed of improperly. The improper dumping and recycling of e-waste in several African countries serve as a major contributor to the release of harmful substances. These hazardous substances can contaminate the environment, leading to adverse effects on human health and ecosystems (Lebbie et al., 2021).

Numerous studies have established associations between e-waste recycling activities and a range of adverse health effects. These effects include negative birth outcomes, such as preterm birth and low birth weight, as well as impaired neurological and behavioural development in children. Additionally, exposure to e-waste has been linked to impaired thyroid function and an increased risk of chronic diseases later in life (Parvez et al., 2021).

It is widely recognized that all individuals engaged in informal e-waste recycling face substantial exposure. However, children are particularly vulnerable to the exposure of hazardous chemicals released during informal or unregulated e-waste recycling activities (Ohajinwa et al., 2019). In addition to the well-known hazardous substances present in e-waste, there are various other chemicals for which limited information is available. E-waste often contains complex mixtures of substances, including flame retardants, plasticizers, heavy metals, and other potentially toxic compounds. The lack of comprehensive data and research on these lesser-known chemicals makes it challenging to fully assess their potential health and environmental impacts (Lebbie et al., 2021).

Electronic products indeed consist of numerous intricate components, many of which contain hazardous chemicals. Prolonged exposure to these chemicals can lead to detrimental effects on the nervous system, kidneys, bones, reproductive system, endocrine system, and may even have carcinogenic properties(Needhidasan *et al.*, 2014).Landfills in African countries that contain e-waste have exhibited elevated levels of various potentially hazardous metals. These metals can include lead, cadmium, mercury, chromium, and others, which pose significant risks to human health and the environment (Kiddee et al., 2013). As mentioned earlier, soils in the vicinity of informal e-waste recycling sites in Nigeria have shown increased concentrations of several heavy metals. These metals include copper, lead, zinc, manganese, nickel, antimony, chromium, and cadmium. The presence of such elevated levels of these metals causes soil contamination(Isimekhai et al., 2017).

Benefit of E-waste

The global e-waste is estimated to contain raw materials with a total value of around 57 billion USD. Among these materials, iron, copper, and gold are considered to be the most significant contributors to this value (Forti et al., 2020). E-waste recycling also recovers valuable materials including iron, aluminium, copper, silver, and rare earth metals but excessive exposure can be noxious (Parvez et al., 2021). E-waste is indeed recognized worldwide as a valuable resource due to the potential for recovering valuable materials from it. These materials include iron, aluminum, copper, gold, silver, and rare earth metals. In many low- to middle-income countries, e-waste serves as a source of much-needed income, as individuals and communities engage in recycling and recovery activities to extract and sell these valuable materials (Asante et al., 2019). The efficient recycling of metals from e-waste plays a vital role in alleviating the pressure on the global supply of these metals, particularly critical metals that are at risk of depletion. By recycling metals from e-waste, we can reduce the reliance on primary mining and extraction, thereby conserving natural resources and ensuring a more sustainable use of these valuable materials. This contributes to a circular economy approach and helps mitigate the risks associated with the limited availability of certain metals in the long term (Yang et al., 2021). It is estimated that the electronics industry consumes approximately 300 tons of gold annually. Gold is widely used in electronic components and circuitry due to its excellent conductivity and corrosion resistance properties. However, the recycling and recovery of gold from e-waste can help reduce the demand for newly mined gold and promote the conservation of this precious metal (Rucevska et al., 2015).

Research Framework

The research framework for the study was based on the Health Belief Model. This model provides a theoretical foundation for understanding how individuals' beliefs, perceptions, and attitudes influence their health-related behaviours. By applying the Health Belief Model, the study aimed to explore how factors such as perceived vulnerability, perceived benefits, and other variables influenced e-waste management practices among the electronic technicians.

The Health Belief Model (HBM) is indeed one of the most widely utilized theories in health education and promotion. It has been extensively applied in various contexts to understand and explain health-related behaviors, including preventive behaviors, health promotion, and adherence to treatment regimens. The HBM provides a valuable framework for understanding individuals' perceptions, beliefs, and motivations regarding health-related actions, facilitating the development of effective interventions and strategies to promote positive health behaviors.(Stretcher & Rosenstock, 1997). The Health Belief

Model (HBM) was developed in the early 1950s by Hochbaum, Kegeles, Leventhal, and Rosenstock. This model was created to elucidate health-related behaviors at the level of individual decision-making(Rosenstock, 1966).

It considers various factors, such as an individual's perceived susceptibility to a health threat, perceived severity of the threat, perceived benefits, and barriers to taking action, and cues to action, in order to understand and predict health-related behaviours.

The concepts of the Health Belief Model (HBM) have demonstrated stability and applicability across various research and practical settings(Rawlett, 2011). In its original formulation, the Health Belief Model (HBM) identified four core concepts that elucidate health-related behaviour: perceived susceptibility, perceived severity, perceived benefits, and perceived barriers.(Holwerda, 2000).

Therefore, in this study, the determinants of e-waste management practice are based on the concepts of perceived vulnerability and benefits derived from the Health Belief Model (HBM). These concepts are employed to examine how individuals' perceptions of their susceptibility to e-waste hazards and the perceived benefits of proper e-waste management influence their actual practices in handling e-waste. as depicted in Figure 1.

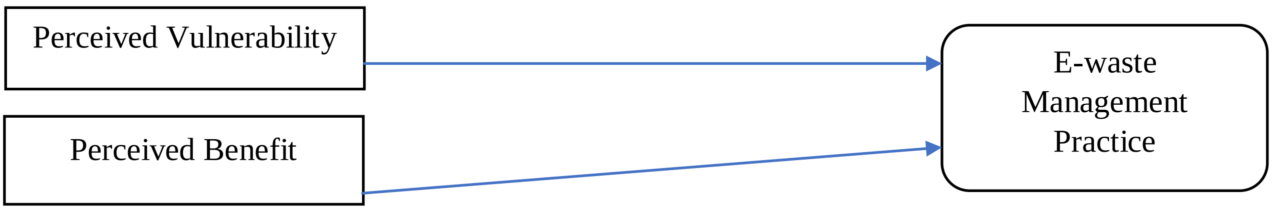

*Figure 1:*Research framework

Adults who are involved in the dismantling and handling of e-waste are exposed to varying degrees of toxic substances, depending on the level of exposure and protective measures. However, it is widely recognized that children are even more vulnerable to the harmful effects of e-waste due to their developing organs, lower immunity, and unique behavioural patterns(Umair et al., 2015). In June 1988, a massive amount of 4,000 tons of e-waste was unlawfully disposed of in the Koko area of Delta State, Nigeria.Tragically, the landlord of the affected field, who was directly exposed to these hazardous materials, experienced adverse health effects and eventually succumbed to cancer (Obaje, 2013). The involvement of children in the e-waste recycling industry contributes to their vulnerability and exposes them to various risks(Perkins et al., 2014).

Lead is one of the major heavy metal contaminants during the process of e-waste recycling or dismantling.Children, in particular, are more vulnerable to lead poisoning compared to adults due to several factors.(Zheng *et al.*, 2008). According to the findings of a study conducted by Adaramodu *et al.* (2012), electronic dealers who store e-wastes and consumers who frequent visit the electronics market face a potential risk of zinc toxicity.

The results from quantitative reviews of the HBM, suggest that the primary variables (susceptibility, severity, benefits, and barriers) were significant predictors of health-related behaviour in most cases (Orji et al., 2012). Thus, it is hypothesized that:

Hypothesis 1: Perceived Vulnerability significantly influence e-waste management practice**.**

E-waste contains precious and special metals, including gold, silver, palladium and platinum (Namias, 2013). The findings of a preliminary study, revealed that refurbishing, collection, and recycling of used and obsolete e-products provide extensive employment opportunities (UNEP, 2012). On a broader scale, analysing the environmental and societal impacts of e-waste reveals a mosaic of benefits and costs (Iles, 2004). Augoustinos (2013) found that individuals with a high perceived benefit were more likely to have good adaptive behaviours during a heat wave. In another study Orji *et al.* (2012) found that perceive benefit was a predictor of behaviour. Hence, the study postulated that:

Hypothesis 2: Perceived Benefit significantly influence e-waste management practice.

3. Methodology

The population of the study consisted of all electronic technicians residing within Bauchi metropolis who were engaged in the repair of computers, GSM devices, and televisions. The total number of individuals in this population was 805.The study utilized a sample size of 265, which was determined using the method proposed by Krejcie and Morgan, (1970).Out of the total questionnaire administered, 248 (representing 93.6% of the sample) were used for analysis in the study.
The items used as a measure for perceived vulnerability and benefit were adapted from HBM (Champion, 1993). And the items used as a measure for the dependent variable (e-waste management practice) were adapted from (Pradeep Kumar *et al.*, 2013; Shah, 2014; Sikdar & Vaniya, 2014). The variables in the study were measured using a five-point Likert scale, where respondents provided their level of agreement or disagreement on a range from Strongly Disagree (1) to Strongly Agree (5).
Moreover, the research model was evaluated using Partial Least Squares-Structural Equation Modeling (PLS-SEM). PLS-SEM was chosen as the analytical method because it is suitable for studies with small sample sizes, non-normally distributed data, and when the primary focus is on predicting and explaining target constructs(Hair et al., 2014).

Results

Statistical procedures were applied to address missing data as well as univariate and multivariate outliers as suggested by Sekaran, (2003), Tabachnick and Fidell, (2007). Finally, the study tested the assumption of univariate analysis using skewness, kurtosis and Kolmogorov Smirnov as stipulated by Hair, Black, Babin and Anderson (2010). The normality test conducted on the data indicated no significant deviation from normal distribution. Multivariate normality was assessed by examining the histogram of multiple regression, which suggested that the data under study followed a normal distribution. This observation was further validated through visual inspection of the histogram, which confirmed the normal distribution of the data. The next assumption which is homoscedasticity is related to the assumption of normality because when the assumption of multivariate normality is met, the relationships between variables are homoscedastic. The Normal P-P Plot analysis conducted in the study demonstrates that the data points closely align along a diagonal line, from the bottom left to the top right. This alignment suggests that the assumption of linearity is met, indicating a linear relationship between the variables being analysed.
Research model assessment in PLS is categorized into two stages: structural model (inner) model and measurement models (outer) model. The structural model represents constructs in circles or ovals and

displays the relationships (paths) between the constructs while the measurement model display the relationships between the constructs and the indicator variables (rectangles) (Hair *et al.*, 2014).

Measurement model Assessment

PLS SEM, uses outer loading and composite reliability to assess indicator reliability and internal consistency respectively. While Average Variance Extracted (AVE) is used to evaluate convergent validity and finally square root of AVE (Fornell-Larcker criterion) is used to evaluate discriminant validity. According to Hair *et al.* (2014) outer loading for individual indicator should be greater than 0.70, although indicators with loadings between 0.40 and 0.70 should be considered for deletion only when deleting it can lead to an increase in the composite reliability or the average variance extracted above the suggested cut-off value. It can be observed from table 1 that most of the loadings are above the predetermined threshold. This indicates that the indicators have a strong association with their corresponding latent constructs and contribute significantly to the measurement of those constructs.

Table 1: Internal Consistency and Convergent Validity

Constructs	Indicators (Items)	Loadings	AVE	Composite Reliability
Perceived Vulnerability	PV1	0.678	0.577	0.803
	PV2	0.764		
	PV3	0.830		
Perceived Benefit	PB1	0.660	0.525	0.767
	PB2	0.793		
	PB4	0.713		
E-waste MP	EMP3	0.747	0.507	0.752
	EMP4	0.786		
	EMP5	**0.585**		

Similarly, item reliability, composite reliability, and average variance extracted (AVE) are essential measures for evaluating convergent validity. Among these measures, AVE is the predominant factor, as it has a threshold value greater than 0.5. AVE quantifies the amount of variance captured by the latent construct, indicating the convergent validity of the measurement model (Hair *et al.*, 2014). The items' reliability and composite reliability requirements are completely fulfilled, indicating the robustness and consistency of the measurement model. These reliability measures assess the internal consistency and stability of the indicators and constructs in the study, indicating that the items are reliable and accurately measure the latent variables under investigation. The study maintains a satisfactory level of convergent validity as all constructs have AVE values above the suggested threshold of 0.50. This indicates that a substantial proportion of the variance in the observed indicators is captured by their corresponding latent constructs. The higher AVE values suggest that the constructs are reliable and valid representations of the underlying concepts they are intended to measure as depicted in table 1.

Additionally, Fornell and Larcker (1981)proposed that the square root of the AVE (Average Variance Extracted) for each construct should be greater than the correlations between that construct and other constructs. This criterion ensures discriminant validity, indicating that each construct is distinct and measures a unique aspect of the phenomenon under study.

As depicted in Table 2, the diagonal values (square root of AVE) are higher than the values in their corresponding rows and columns. This pattern indicates that the requirement for discriminant validity is met. The higher diagonal values suggest that each construct has more shared variance with its own indicators than with indicators of other constructs. This confirms that the constructs are distinct and distinguishable from one another, supporting discriminant validity in the measurement model.

Table 2: Discriminant Validity (Fornell-Larcker Criterion)

Construct	PV	PB	EMP
PV	**0.760**		
PB	0.232	**0.724**	
EMP	0.237	0.374	**0.712**

Structural (Inner) Model Assessment

After establishing the validity and reliability of the measurement model, the subsequent step involves assessing the structural model. The structural model examines the relationships between the latent constructs and tests the proposed hypotheses or paths in the research model. This analysis helps to determine the strength and significance of the relationships between the variables and provides insights into the underlying theoretical framework. It deals with the model's predictive abilities and the relationships between constructs (Hair *et al.*, 2014). Significance of the path coefficients, level of coefficient of determination (R^2), the effect size (f^2) of the exogenous variables, the predictive relevance (Q^2), and the effect size (q^2) of the Q^2 are key criteria for evaluating structural model in PLS-SEM (Hair *et al.*, 2014). Since path coefficients are estimated in Partial Least Squares (PLS) using Ordinary Least Squares (OLS) regression, it is crucial to assess the level of collinearity among predictor variables. This assessment is necessary to ensure that the results are not biased and can be interpreted accurately. High collinearity between predictor variables can lead to unstable and unreliable estimates of the path coefficients. Therefore, diagnostic tests for collinearity, such as variance inflation factor (VIF) analysis, is required to identify and mitigate any potential issues arising from collinearity in the model. This helps to ensure the validity and robustness of the results obtained from the analysis(Hair *et al.*, 2014). According to Hair *et al.* (2014) multicollinearity exist if Variance Inflation Factor VIF of a given exogenous variable is above 5 (i.e. VIF > 5). Table 4 shows that there was no evidence of multicollinearity amongst the exogenous variable.

Predictive Relevance of the Model

The coefficient of determination (R^2) is widely used as a measure to evaluate the goodness-of-fit of a structural model. R^2 indicates the proportion of variance in the dependent variable that can be explained by the independent variables in the model(Hair *et al.*, 2014). Cohen, (1988) recommended R^2 values between 0.10 to 0.29 as small, 0.30 to 0.49 as medium, and 0.50 to 1.0 as large. As indicated in Table 3, the R^2 value for this study was found to be 0.250. This means that 25% of the variance in e-waste management practice is explained by the exogenous variables. Furthermore, based on the rules of thumb mentioned earlier, the R2 value of 0.250 indicates that the model has a small predictive power.

Moreover,Hair *et al.*, (2014) suggested that exogenous (f^2) values of 0.02, 0.15, and 0.35 indicate small, medium, or large effect, respectively, on an endogenous construct.
Based on the result presented in table 3, PV (f^2 = 0.008) have effect size below the minimum threshold of 0.02, thus it has no impact on the endogenous variable when omitted. However, PB (f^2 = 0.06) has small impact on the endogenous variable when omitted.
Furthermore, the study employed a blindfolding procedure to obtain the Q^2 measure. This was done by excluding the 9th data points from the indicators of the endogenous construct. The purpose of this procedure is to assess the predictive relevance of the model by examining how well it can predict the omitted data points. By comparing the predicted values with the actual values of the omitted data points, the Q^2 measure provides an estimation of the model's predictive accuracy.According to Fornell and Cha (1994), the cross-validated redundancy (cv-red) value serves as an indicator of the predictive relevance of a model. A cv-red > 0 suggests that the model has predictive relevance, meaning it can accurately predict the outcome variable beyond chance. On the other hand, a cv-red < 0 indicates a lack of predictive relevance, suggesting that the model is unable to predict the outcome variable better than random chance
As shown in Table 3, the Q^2 value of 0.115 indicates substantial evidence of predictive relevance for the model. Similarly, the result in table 3 showed that PB (q^2 = 0.027) have small effect size since $q^2$is slightly above the minimum threshold of 0.02, thereby having small predictive impact on the endogenous variable. On the contrary, PV (q^2 = 0.001) have effect size of predictive relevance below the minimum threshold of 0.02, thus it has no predictive impact on the endogenous variable.

Table 3: Model Quality Statistics

Endogenous Construct	Exogenous Constructs	R2	Q2	Effect **Sizes-R^2 (f^2)**	**Effect Sizes-Q^2 (q^2)**
	PV			0.008	0.001
EMP	PB	0.250	0.115	0.06	0.027

Hypotheses Testing
Hypothesis testing in SmartPLS is typically conducted using the standard bootstrapping procedure with a specified number of subsamples. In this case, 5,000 subsamples were used for the bootstrapping process. The significance of paths coefficients of the study were obtained through t-value (t ≥1.96) and p-value ($p < 0.05$) as suggested by (Hair et al., 2011).
The result in table 4, reveals that Perceived Benefit (β=0.247, std. error=0.057, t= 4.306, p 0.000) have positive and significant influence on E-waste Management Practice. While Perceived Vulnerability (β=0.085, std. error= 0.064, t-value= 1.332, p 0.183) have no significant influence on E-waste Management Practice. Therefore, hypothesis 2is accepted whereas hypothesis 1 and is rejected.

Table 4: Hypotheses Testing

Hypothesis	**Path Coefficient**	**Std Error**	**t-values**	**P Values**	**VIF**	**Decision**
Perceived Vulnerability -> E-waste MP	0.085	0.064	1.332	0.183	1.122	Rejected

Perceived Benefit -> E-waste MP	0.247	0.057	4.306	0.000	1.151	Accepted

4. Discussion of Results

All the variables examined in this study demonstrate good reliability, convergent validity, and discriminant validity. The reliability analysis indicates that the measurement items reliably measure their intended constructs, ensuring consistency and stability in the measurement model. The assessment of convergent validity reveals that the variables have a strong association with their respective constructs, as evidenced by high factor loadings and satisfactory average variance extracted (AVE) values. Moreover, the analysis of discriminant validity confirms that each construct is distinct from others, as indicated by the higher square root of AVE values compared to the inter-construct correlations. Overall, these findings support the reliability, convergent validity, and discriminant validity of the variables, instilling confidence in the measurement model's robustness and accuracy.

The result of the first hypothesis ($\beta = 0.085$, t-value = 1.332, $p > 0.05$) showed an insignificant relationship which is contrary to some related findings in prior studies. For example, the personal perception of risk or vulnerability has been found to be an important perception in promoting the adoption of healthier behaviours (Orji *et al.*, 2012). Also studies have shown that individual who believed they had risk factors for cervical cancer were more likely to take action to prevent an adverse outcome subsequent to getting the disease (Saslow *et al.*, 2002).

Although, there are studies that support the findings of the first hypothesis. For instance, Morris (2012) stated that when an individual perceives a threat as not serious or themselves as unsusceptible to it, they are unlikely to adopt mitigating behaviours. This could be the possible reason for having an insignificant relationship between e-waste vulnerability and e-waste management practice.

The second hypothesis ($\beta = 0.247$, t-value = 4.306, $p < 0.05$) as depicted in table 4 suggests that perceived Benefit significantly influence e-waste management practice. Meaning that the more electronic technicians perceive the benefit of e-waste, the more it will influence their proper e-waste management practice. This finding is in compliance with other related researches. For instance a study by Augoustinos (2013) found that individuals with a high perceived benefit were more likely to have good adaptive behaviours during a heat wave. Also, a study by Orji *et al.* (2012) showed that perceive benefit was a predictor of behaviour. Additionally, the result of a study by Fararah and Al-swidi (2013) also show that perceived benefits have a positive and significant effect on the satisfaction of customers.

5. Conclusion

The study was able to ascertain possible factor that influences e-waste management practice.The reliability and validity of the scales were ensured in this study through rigorous testing and analysis. Hypothesis H2 was supported in this study, as the results indicated a significant effect of Perceived Benefit on e-waste management practice. This suggests that individuals who perceive greater benefits associated with e-waste management are more likely to engage in proper practices and take actions to manage e-waste effectively.Though hypotheses H1 do not have significant effect on e-waste management practice. Overall, the study achieved an R2 value of 0.250, indicating that 25% of the variance in e-waste management practice was explained by the independent variables included in the model. This means that the factors considered in the study, such as perceived vulnerability, perceived benefit, and other relevant variables, accounted for a significant portion of the variability observed in e-waste management practices. However, it is important to note that there are other factors not included in the model that may also contribute to e-waste management practices. In terms of the individual contribution of the independent variables, the results indicate that Perceived Benefit (β = 0.247) has the highest impact on e-waste management practice. The higher the perceived benefit, the more likely individuals are to adopt proper e-waste management behaviours.Furthermore, the results of the study indicate that the research model has substantial evidence of predictive relevance, as evidenced by the Q2 value of 0.115. This suggests that the model can accurately predict and explain the variance in e-waste management practice among electronic technicians in Bauchi metropolis. The findings specifically highlight the significant influence of Perceived Benefit on e-waste management practice, indicating that individuals who perceive greater benefits associated with proper e-waste management are more likely to engage in responsible practices.

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