05, 06, 07 e 08 de novembro de 2024
ISSN 2177-3866

ANTECEDENTS OF ELECTRONIC WASTE RECYCLING: analysis of planned behavior and protection motivation

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1 INTRODUCTION

Electronic waste has become a global environmental issue that has attracted the attention of many countries in recent years (Delcea et al., 2020, Wagner et al., 2022). Economically, recycling this waste can yield a wide variety of valuable and precious materials, such as palladium, copper, iron, gold, aluminum, platinum, and silver (Aboelmaged, 2021. Wagner et al., 2022).

About 97 percent of electronic waste in Latin America is not formally collected or sent to appropriate recycling facilities (Wagner et al., 2022). The end consumer plays an important role in the supervision and selective household collection of electronic waste, as disposal at specific collection points for this type of waste will promote the reuse of base metals or precious metals, as well as other materials that can be reused (Arain et al., 2020; Sobrinho et al., 2019).

The problem of solid waste disposal requires a solution at local, national, and international levels. Technological advances are one part of the equation. The other part is human behavior and decision-making related to recycling (Kothe et al., 2019).

As the transition to sustainability takes hold, recycling emerges as one of the fundamental concepts of sustainable behavior (Phulwani et al., 2020). Thus, research on recycling behavior is receiving great attention in various fields, due to the growing prioritization of resource recovery and management (Albuquerque et al., 2021; Li et al., 2019; Phulwani et al., 2020).

When analyzing the determinants of pro-environmental behavior, multiple factors must be considered. In this context, many studies emphasize that psychosocial factors contribute more to understanding the mechanisms of pro-environmental behavior compared to sociodemographic data and other external factors (Aboelmaged, 2021; Li et al., 2019, Strydom, 2018, Tweneboah-Koduah et al., 2020).

The question of why people recycle or do not recycle has long been a part of the lives of researchers and professionals seeking to understand and influence this and other pro-environmental behaviors (Thomas & Sharp, 2013, Strydom, 2018, Aboelmaged, 2021). Recognizing the plurality of influences in shaping electronic waste recycling behavior, a thorough analysis of the topic is necessary, utilizing comprehensive theoretical lenses such as those proposed by the theory of planned behavior (TPB) and the protection motivation theory (PMT). The TPB was developed by Ajzen (1991). The TPB can be characterized by several features that can help explain its widespread use as a model for predicting and changing behavior Ajzen (2020).

Regarding PMT, it was originally developed by Rogers (1975) and later revised by Maddux and Rogers (1983). PMT proposes motivational factors that can influence individuals' environmental awareness (Jang & Lee, 2022; Janmaimool, 2017). In recent years, the theory has evolved and has been applied in studies aiming to analyze the determinants of pro-environmental behavior (Shafiei & Maleksaeidi, 2020, Tchetchik et al., 2021, Jang & Lee, 2022). Additionally, a distinguishing feature of PMT is its use of the concept of risk, which can be assessed using the constructs proposed within the theory, a concept absent in TPB (Jansen & Van Schaik, 2017, Jang & Lee, 2022).

Given the contextualization, the following research question arises: What are the factors that influence electronic waste recycling behavior? To answer this question, the general objective of this study is to analyze the antecedents of electronic waste recycling behavior in light of the theory of planned behavior and the protection motivation theory. To achieve this purpose, a theoretical review was conducted, encompassing the TPB, the PMT, and the topic of electronic waste. This research is classified as explanatory, descriptive, and quantitative in approach.

This research will use both theories to bring new understandings to the topic that will be studied. The combination of multiple theories has great potential value. As the author emphasizes, new combinations of theories or concepts can produce new perspectives and new research agendas (Cairney, 2013).

2 THEORETICAL FOUNDATION

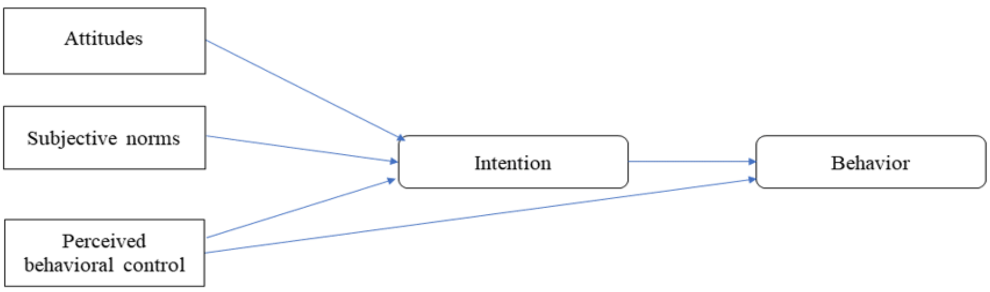
2.1 Theory of planned behavior

Over the years, various theoretical perspectives have been applied to study human behavior and determine the antecedent factors of behaviors. The TPB was initially proposed by Ajzen (1991). The TPB posits that a person's intention to perform (or not perform) a behavior is the most important immediate determinant of that action (Ajzen, 1991, 2020).

The TPB is based on the assumption that individuals tend to behave in a generally sensible manner, taking into account the information available to them and implicitly or explicitly weighing the implications of their actions (Ajzen, 1991, 2005). In the TPB, individuals' actions are determined by their intentions and perceptions of control, in the sense that their intentions are influenced by attitudes toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 2005, 2020).

Figure 1

Theory of Planned Behavior.



Source: Adapted from Ajzen (1991).

For some intentions, attitudinal considerations are more important than normative considerations, while for other intentions, normative considerations are predominant (Aboelmaged, 2021; Ajzen, 2020; Tweneboah-Koduah et al., 2020). Similarly, perceived behavioral control is more important for some behaviors than for others (Strydom, 2018).

In some cases, only one or two factors are needed to explain the intention. However, in other cases, all three factors (attitudes, subjective norms, perceived behavioral control) are necessary to explain the intention (Ajzen, 1991, 2020). Moreover, the weight of these three factors can vary from person to person, from one group to another, and from one population to another (Ajzen, 2005).

In general terms, attitudes toward a behavior indicate the individual's evaluation of the action under study, ranging from negative to positive (Aboelmaged, 2021; Ajzen, 2020; Echegaray & Hansstein, 2017). Subjective norm corresponds to the degree of an individual's perception of social desirability to perform the action (Ajzen, 2005; Echegaray & Hansstein, 2017). Perceived behavioral control includes measures of self-efficacy and perceived control and indicates how well an individual feels he or she can overcome obstacles or take advantage of facilitators when performing an action (Echegaray & Hansstein, 2017; Strydom, 2018).

2.1.1 Attitude

The construct of attitude occupies a central place in theories and research on consumer behavior (Aboelmaged, 2021; Yuriev et al., 2020). Attitude can be defined as a disposition to be in favor of or against, in a positive or negative way, a behavior of interest (Ajzen, 2005; Ajzen et al., 2008; Yuriev et al., 2020).

Over the years, studies have shown substantial evidence that attitudes generally have a moderately positive influence on pro-environmental behavior (Cerri et al., 2018; Echegaray & Hansstein, 2017). This evidence can also be seen in the works of Gkargkavouzi et al. (2019) and Aboelmaged (2021).

According to Aboelmaged (2021), attitude has a positive effect on the intention to recycle electronic waste. This effect consolidates the strong role of attitudes in influencing the intention to engage in pro-environmental behaviors (Aboelmaged, 2021). For Ajzen (1991), if people have favorable attitudes toward certain behaviors, they are more likely to perform them. The studies by Tweneboah-Koduah et al. (2020) highlight that, regarding waste disposal behavior, attitude is the strongest predictor of behavior, followed by subjective norm and intention. Thus, the first hypothesis was formulated:

H1: Attitudes have a positive influence on the intention to recycle electronic waste.

2.1.2 Subjective norms

The second determinant, which precedes intention, is the influence of social pressure to perform or not perform a particular behavior. Since this determinant deals with perceived normative prescriptions, it is called "subjective norms" (Ajzen, 2005). Complementarily, Kim et al. (2009) and Hua and Wang (2019) state that subjective norms reflect how individuals are affected by the influence of their reference group (family, friends, neighbors, culture, religion, etc.).

Regarding subjective norms, they can be formed by two types of normative beliefs: injunctive and descriptive. A preliminary rule of injunctive belief is the expectation or subjective probability that a particular referent individual or group (e.g., friends, family, spouse, coworkers, or supervisor) approves or disapproves of the behavior in question (Ajzen, 1991, 2020). Descriptive normative beliefs, on the other hand, are beliefs about whether the reference group engages in the behavior in question (Ajzen, 1991, 2020). Both types of beliefs contribute to the perceived social pressure to engage in the behavior or subjective norms (Ajzen, 2020).

The correlation that subjective norms affect behavioral intentions and create actual behavior has been discussed in many studies (Aboelmaged, 2021; Borthakur & Govind, 2018; Echegaray & Hansstein, 2017; Li et al., 2019). Based on the study by Echegaray and Hansstein (2017), which analyzed the antecedents of pro-environmental behavior through the theory of planned behavior that can influence the electronic waste recycling process, it was found that subjective norms have a positive relationship with the intention to recycle (Borthakur & Govind, 2018; Echegaray & Hansstein, 2017; Li et al., 2019). Thus, the second hypothesis was formulated:

H2: Subjective norms have a positive influence on the intention to recycle electronic waste.

2.1.3 Perceived behavioral control

The third determinant is perceived behavioral control. The importance of behavioral control is self-evident: the resources and opportunities available to a person should, to some extent, dictate the likelihood of behavioral performance (Ajzen, 1991).

Ajzen (2020) emphasizes that just as attitudes are based on accessible behavioral beliefs, subjective norms are based on accessible normative beliefs, while perceived behavioral control is based on accessible control beliefs (Ajzen, 1991, 2020). These beliefs pertain to the presence of factors that can facilitate or hinder the performance of the behavior.

Control belief is defined as a person's subjective probability that a particular facilitating or inhibiting factor will be present in the situation of interest (Ajzen, 1991). Each control belief contributes to perceived behavioral control in interaction with the perceived power of the factor to facilitate or impede the performance of the desired behavior (Ajzen, 2020).

When perceived behavioral control is the most influential behavioral antecedent for individuals, it is necessary to reduce the barriers that prevent the execution of the studied behavior to make individuals feel more capable of performing a particular action (Yuriev et al., 2020).

Previous studies emphasize that perceived behavioral control has a positive relationship with individuals' intention to recycle materials (Echegaray & Hansstein, 2017; Li et al., 2019). When analyzing perceived behavioral control as an antecedent of waste recycling behavior, recent studies have found that perceived behavioral control has a strong positive relationship with the intention to recycle waste (Liu et al., 2021; Strydom, 2018). Given the above, the third hypothesis of the present study was formulated:

H3: Perceived behavioral control has a positive influence on the intention to recycle electronic waste.

2.1.4 Intention

A central factor in the theory of planned behavior is an individual's intention to perform a particular behavior. Intentions are assumed to capture the motivational factors that influence a behavior, that is, they are indications of how hard people are willing to try and how much effort they plan to exert in order to perform a particular behavior (Ajzen, 1991, 2005).

The TPB posits that behavioral intention is considered the closest predictor of behavior (Liu et al., 2021). In the same vein, it emphasizes that, essentially, TPB posits that the stronger the behavioral intentions, the greater the likelihood that a specific behavior will be performed (Soomro et al., 2022). People's intentions depend on their motivation to fulfill what they believe to be a desired action, how they feel, and what is expected of them (Strydom, 2018).

Mohammed et al. (2022) emphasize that individuals may develop a greater intention to recycle electronic waste if there is availability of time, low costs involved, and nearby recycling facilities (Mohammed et al., 2022). Therefore, making recycling more convenient increases the likelihood of recycling intention and behavior among consumers.

Although many studies consider behavioral intention as the greatest predictor of the behavior in question (Albomaged, 2021; Mohamad et al., 2022; Soomro et al., 2022; Strydom, 2018), it is stated that researchers can only justify the use of intention as the main antecedent for behavior if there is independent evidence of a strong intention-behavior correlation in the population in question (Ajzen, 2020). Thus, according to the Theory of Planned Behavior (TPB), the performance of a behavior is a joint function of intentions and perceived behavioral control (Ajzen, 1995, 2020).

Intentions and perceptions of control must be evaluated concerning the particular behavior of interest, and the specified context must be the same as where the behavior is to occur (Ajzen, 1991; Ajzen, 2020). Based on the information discussed, the following hypotheses were formulated:

H4: Perceived behavioral control has a positive influence on electronic waste recycling behavior.

H5: Intention has a positive influence on electronic waste recycling behavior.

2.2 Protection motivation theory

The Protection Motivation Theory (PMT) proposes a framework to explain the factors that predict preventive risk behaviors based on society's motivation to protect itself from threats such as natural disasters and climate change (Maddux & Rogers, 1983). In recent years, PMT has been adapted and applied in studies to determine people's pro-environmental behavior (Jang & Lee, 2022; Janmaimool, 2017).

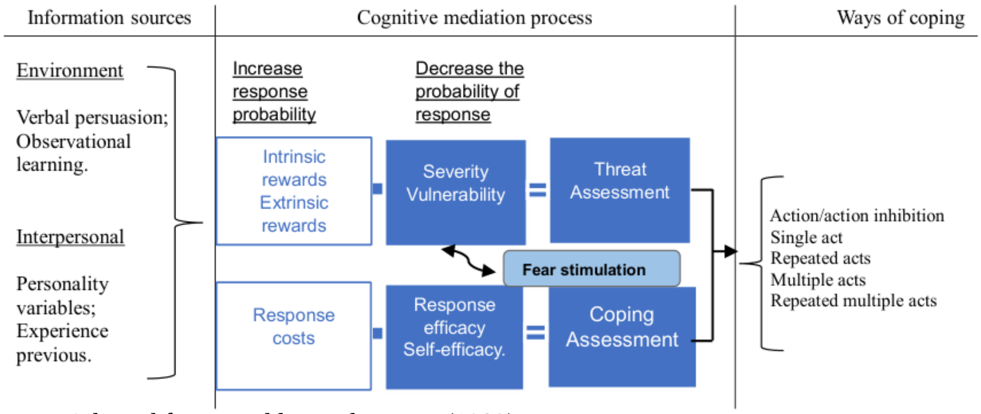
The PMT specifies the cognitive processes through which individuals go after receiving information about threats. These processes result in the individual's motivation to engage in adaptive actions or maladaptive behaviors (Rogers & Prentice-Dunn, 1997). Adaptive responses are those that effectively minimize the threat, while maladaptive responses are those that help reduce the fear an individual may feel toward a danger but fail to reduce the occurrence and/or effects of the actual danger (Maddux & Rogers, 1983; Rippetoe & Rogers, 1987).

According to Prentice-Dunn and Rogers (1986), although the PMT was originally proposed to provide conceptual clarity for understanding fear appeals in people's behavior, the PMT emphasizes the cognitive processes that mediate attitudes and behavioral changes (Maddux & Rogers, 1983).

The PMT assumes that individuals intend to engage in protective behavior (adaptive response) when facing a threatening event if they believe that inaction would pose a threat to them (high threat appraisal) and that performing the protective behavior would mitigate this threat (high coping appraisal) (Kothe et al., 2019). The PMT is suitable for application in different contexts and can be used in studies addressing sustainable consumption and/or waste recycling (Tchetchik et al., 2021). Along the same lines, Jang and Lee (2022) emphasize that, in recent years, the PMT has been applied to environmental issues, including various problems involving waste management and recycling.

Figure 2

Protection Motivation Theory.



Source: Adapted from Maddux and Rogers (1983).

Two assessment processes are central to the theory: threat appraisal and coping appraisal. According to Maddux and Rogers (1983), the threat appraisal process is responsible for evaluating factors that increase or decrease the likelihood of making the maladaptive response. As Bubeck et al., (2012) state, "threat appraisal" describes how an individual evaluates how threatened they feel by a certain risk. Threat appraisal is composed of the variables "perceived vulnerability" (probability), "perceived severity" (consequences), and "intrinsic and extrinsic rewards”.

The variables that increase the likelihood of the maladaptive response are intrinsic rewards (physical and psychological pleasure) and extrinsic rewards (social approval) (Maddux & Rogers, 1983). A considerable amount of studies indicates that these variables have a negative and non-significant relationship with individuals' behavioral intention (Bockarjova & Steg, 2014; Kothe et al., 2019; Rogers & Prentice-Dunn, 1997; Shafiei & Maleksaeidi, 2020). Thus, the present research will not include intrinsic and extrinsic rewards in the theoretical model to be applied.

Regarding response costs, previous studies state that if the cost of the proposed behavior is high, the person is likely to avoid engaging in that behavior. In other words, the higher the response cost, the lower the chance of an individual expressing the intention to perform a particular behavior (Janmaimool, 2017; McClendon & Prentice-Dunn, 2001).

Studies applying the PMT to pro-environmental behavior have pointed to a negative influence between response costs and behavioral intention (Bockarjova & Steg, 2014; Shafiei & Maleksaeidi, 2020). Additionally, recent studies using the PMT to analyze people's pro-environmental behavior no longer apply the constructs of response costs and intrinsic and extrinsic rewards (Jang & Lee, 2022; Tchetchik, et al., 2021). Therefore, the construct of response cost, as well as intrinsic and extrinsic rewards, will not be addressed in the theoretical model of this research.

2.2.1 Perceived vulnerability and perceived severity

According to Bockarjova and Steg (2014), perceived vulnerability reflects perceptions of how an individual might be susceptible to the existing threat. Thus, perceived vulnerability measures individuals' perceptions of fragility in various everyday situations (Shafiei & Maleksaeidi, 2020).

Maddux and Rogers (1983) state that perceived severity reflects how the gravity of an existing risk is perceived. In other words, perceived severity will make an individual more cautious if they believe the damage from the threat is high. For example, if people think that long-term garbage storage at home could harm their health, they will tend to avoid such practice (Janmaimool, 2017; Prentice-Dunn & Rogers, 1986). According to the theory and previous research in which the PMT was applied, higher perceived vulnerability and severity correspond to a greater intention of individuals to perform a particular behavior (Jang & Lee, 2022; Prentice-Dunn & Rogers, 1986; Tchetchik et al., 2021).

The studies conducted by Jang and Lee (2022) used the protection motivation theory to analyze whether an individual's perception of food waste problems affects their purchase intention. The data analyzed by the authors also demonstrated that perceived vulnerability has a positive relationship with the behavior of purchasing nutritious foods. Additionally, Tchetchik et al., (2021) identified that both perceived severity and perceived vulnerability have a positive relationship with pro-environmental behavior. Thus, the following hypotheses were formulated:

H6: Perceived vulnerability has a positive influence on electronic waste recycling behavior.

H7: Perceived severity has a positive influence on electronic waste recycling behavior.

2.2.2 Response efficacy and self-efficacy

Coping appraisal partially consists of judgments about the efficacy of a preventive response that will avoid the perceived threat (response efficacy) plus the evaluation of the ability to successfully initiate and complete the adaptive response (self-efficacy) (Maddux & Rogers, 1983).

Prentice-Dunn and Rogers (1986) highlight that a person with a strong sense of self-efficacy can easily overcome any barriers (inconvenience, expense), while a person with a weak sense of self-efficacy may be hindered by the same barriers. Self-efficacy influences not only the initiation of the coping response but also the amount of energy expended and the persistence of the person in the face of obstacles to be overcome (Maddux & Rogers, 1983; Prentice-Dunn & Rogers, 1986). Furthermore, studies indicate that higher response efficacy and self-efficacy predict a greater intention to engage in pro-environmental behavior (Kothe et al., 2019; Shafiei & Maleksaeidi, 2020; Tchetchik et al., 2021).

Tchetchik et al., (2021) conducted a study that sought to relate waste recycling and consumption reduction after the restrictions imposed by the Israeli government during the COVID-19 pandemic. The study applied the PMT to investigate threat appraisal and coping appraisal as potential motivators of behavioral changes. Based on the results obtained in their study, coping appraisal (response efficacy and self-efficacy) was positively correlated with the increase in pro-environmental behavioral intention (Tchetchik et al., 2021). Therefore, the following hypotheses were formulated:

H8: Response efficacy has a positive influence on the behavioral intention to recycle electronic waste.

H9: Self-efficacy has a positive influence on the behavioral intention to recycle electronic waste.

2.3. E-waste

According to Awasthi et al. (2018), waste electrical and electronic equipment (WEEE) is considered one of the fastest-growing waste streams in the world and is becoming an emerging issue due to its adverse consequences on the natural environment and human health (Awasthi et al., 2018).

Although electronic products play a crucial role in the development of a nation, the rapid growth of the electronics industry and the constant technological changes resulting from this advancement in recent years have led to the generation of enormous amounts of electronic waste (Ravindra & Mor, 2019).

Electronic waste generally contains significant amounts of toxic substances and environmentally sensitive materials and can therefore be extremely hazardous to humans and the environment if improperly disposed of and/or recycled (Magalini et al., 2015). In emerging countries like Brazil, the informal sector of electronic waste collection and disposal uses rudimentary methods that affect the proper processing of these materials (Gangwar et al., 2019). In this sense, the informal sector significantly contributes to the elevation of toxic particles extracted from components, particularly levels of heavy metals, through burning and illegal dumping of such waste (Gangwar et al., 2019).

The development of more advanced, faster, and reliable systems has led to a decrease in the product life cycle, prompting consumers to purchase newer and more up-to-date technology products, discarding the older ones (Kumar et al., 2017). However, emerging countries still struggle to implement an effective electronic waste management policy, and as a result, the socio-environmental problems caused by the waste are far from being solved (Yong et al., 2019).

Every year, billions of mobile electronic devices (smartphones, tablets, and laptops) are sold worldwide due to new technological developments emerging daily (Diaz et al., 2016; Wagner et al., 2022). Furthermore, the average time a mobile electronic device is used before being replaced by a newer model is steadily decreasing, meaning that rampant consumption is also one of the aggravating factors in the increase of electronic waste (Diaz et al., 2016; Yuriev et al., 2020). Moreover, each type of electronic waste has a specific size, components, and valuable materials that affect how they should be formally collected, treated, recycled, or disposed of in an environmentally sound manner (Wagner et al., 2022).

3 METHODOLOGY

Regarding its objectives, the research is classified as explanatory and descriptive. According to Prodanov and Freitas (2013), explanatory research is used when the researcher seeks to explain the reasons behind things and their causes through the recording, analysis, classification, and interpretation of observed phenomena.

Descriptive research, in turn, aims to describe the characteristics of a certain population or phenomenon or establish relationships between variables. This involves the use of standardized data collection techniques, such as questionnaires and systematic observation (Prodanov & Freitas, 2013). Regarding its approach, the present research is quantitative, as Marconi & Lakatos (2003) explain that quantitative research allows for an objective, mathematical, and statistical treatment of the collected data, providing measurable results that are more easily testable and verifiable.

The questionnaire was applied between may and june 2023, both in person and online (through dissemination on the authors' social media), using a non-probabilistic cross-sectional sample. According to Freitas et al. (2000), in cross-sectional research, data collection occurs at a single point in time with the aim of describing and analyzing the state of one or several variables. The questionnaire was applied in the city of Maceió, capital of the state of Alagoas. Although the city of Maceió is one of the capitals in the Northeast that has electronic waste collection programs, it is estimated that the state of Alagoas produces around 2,022.08 tons of urban solid waste daily, with 62.49% generated by the population residing in the metropolitan region due to the size of the capital, Maceió (Souza et al., 2020).

Regarding the sample, the number of participants approached to answer the questionnaire was determined by a general rule that the ratio should never be less than 5 to 1, indicating that there must be at least five observations for each item in the applied questionnaire (Hair et al., 2009). Thus, for the present research, based on the number of items in the scales used (33 items), the minimum number of participants was set at 165. After the questionnaire administration period, a sample size of 305 valid responses was obtained. Therefore, the present sample is non-probabilistic. The inclusion criteria for the sample were: availability of the individual to participate in the research, a minimum age of 18 years, residence in the city of Maceió/AL, and internet access (for the online questionnaires).

Regarding the data collection instrument, the validated scales from the studies by Mohamad et al. (2022) and Jang and Lee (2022) were used. In Mohamad et al. (2022) research, the TPB was addressed to study the determinants of consumer intentions and behavior regarding electronic waste recycling in Malaysia. In Jang and Lee's (2022) studies, the authors analyzed the relationships between food waste awareness and the intention to purchase agricultural products. A significant contribution of the study was the application of the PMT as a framework to explain pro-environmental behavior among university students in Iran, allowing for a more in-depth analysis of the antecedents influencing recycling behavior (Jang & Lee, 2022).

The validated scales relevant to the TPB and the PMT were translated and adapted from the aforementioned studies to address the theme of electronic waste recycling and pro-environmental behavior. The scales used can be viewed below.

Table 1

Theory of Planned Behavior Scale and Protection Motivation Theory.

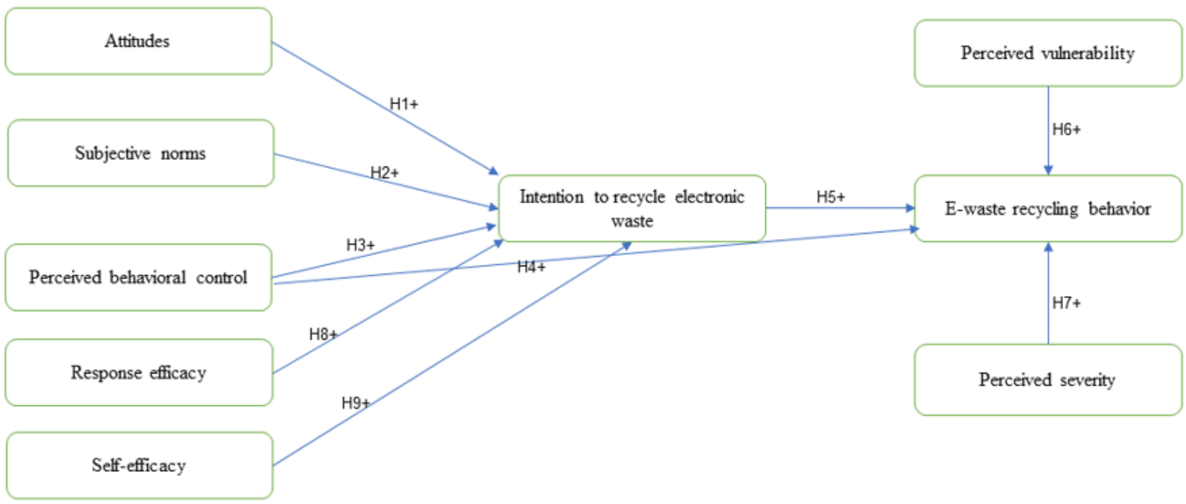
CONSTRUCT CODE	ORIGINAL CONSTRUCTS/ITEMS	AUTHORS
ATT1	E-waste recycling is pleasant	Mohamad et al. (2022)
ATT2	E-waste recycling is responsible	
ATT3	E-waste recycling is good	
ATT4	E-waste recycling is beneficial	
ATT5	E-waste recycling is rewarding	
ATT6	E-waste recycling is sensible	
SN1	My friends expect me to recycle e-waste	
SN2	My classmates or colleagues expect me to recycle e-waste	
SN3	The media influence me to recycle e-waste	
PBC1	I know what items of e-waste can be recycled	
PBC2	I have plenty of opportunities to recycle e-waste	
PBC3	The local council provides satisfactory resources for recycling e-waste	
PBC4	I know where to take my e-waste for recycling	
PBC5	I know how to recycle my e-waste	
INT1	I intend to recycle e-waste regularly	
INT2	I intend to drop-off e-waste at a nearby recycling station	
INT3	I intend to return e-waste to the retailer or the manufacturer	
BEH1	I donate e-waste	
BEH2	I resell e-waste	
BEH3	I store e-waste	
PES1	The problem of environmental pollution caused by the improper disposal of electronic waste is severe.	Jang & Lee (2022)
PES2	When disposing of electronic waste, various harmful substances are generated.	
PES3	Brazil is suffering from environmental pollution due to electronic waste disposal issues.	
PES4	Our surroundings are becoming increasingly polluted by electronic waste.	
PEV1	The improper disposal of electronic waste will eventually have a harmful effect on people.	
PEV2	Improper disposal of electronic waste generates various environmental risks, which are harmful to health.	
PEV3	The problem of improper electronic waste disposal will eventually threaten our lives.	
REE1	Efforts to reduce electronic waste will help prevent environmental pollution.	

REE2	Efforts to reduce electronic waste are effective solutions to prevent environmental pollution.	
REE3	If we try to reduce electronic waste, we can minimize environmental pollution.	
SFE1	I can do enough to reduce electronic waste.	
SFE2	I am confident that I will join in the reduction of electronic waste	
SFE3	I will try to reduce electronic waste.	

The scales used were measured using a Likert scale from 1 to 7 points. After selecting the scales, the theoretical model of the research was constructed.

Figure 3

Theoretical model.



This study used Structural Equation Modeling (SEM) to test the proposed hypotheses. According to Hair et al. (2009), SEM employs a series of measures that describe how well a researcher's theory explains the observed covariance matrix among measured variables. By doing so, it examines the structure of interrelationships expressed in a series of equations, similar to a series of multiple regression equations (Hair et al., 2009). It is noteworthy that such equations describe all relationships between constructs (the dependent and independent variables) involved in the analysis (Hair et al., 2009).

To ensure the validity and reliability of the data, internal consistency indicators (Cronbach's alpha), composite reliability, convergent validity, and discriminant validity were analyzed. Finally, absolute and incremental fit indices were analyzed to support the adequacy of the proposed structural model.

The descriptive analysis of sociodemographic variables and the quantitative analysis of the proposed structural equation model were conducted using the software Statistical Package for the Social Sciences (SPSS) 22.0 and Jeffreys's Amazing Statistics Program (JASP).

4 RESULTS

4.1 Profile of respondents

The sample revealed a higher percentage of female respondents, with a total of 181 (59.3%) responses, compared to 123 (40.3%) male respondents, with 42.3% of the subjects concentrated in the age group of 25 to 34 years. Regarding the level of education, 51.8% of the participants have completed high school, while 35.7% have completed higher education. Respondents with higher levels of education—Master's and postgraduate and doctoral degrees—comprise 10.2% and 2%, respectively, of the study sample. Thus, it can be inferred that the sample has a high level of education, as the combined percentages of those with higher education, master's,postgraduate and doctoral degrees encompass about 47.9%.

Finally, the most common family income (42.6%) in the sample was respondents with a family income above 1 and up to 3 minimum wages, followed by 26.6% of participants with a family income above 3 and up to 6 minimum wages). Therefore, it is evident that although the sample participants have a high level of education, the family income of most respondents is still low.

4.2 Structural model results and discussions

First, before proceeding with the SEM of the proposed model, the obtained data were tested for their distribution to verify if they followed a normal distribution curve. Through the application of the Kolmogorov-Smirnov and Shapiro-Wilk normality tests, it was found that all variables had p-values less than 0.05, indicating that the data do not follow a normal distribution. In this sense, to confirm the validity of the proposed hypotheses, it should be noted that the chosen SEM method was the diagonal weighted least squares (DWLS), which is considered one of the most appropriate techniques for non-normal data in studies involving latent variables (Li, 2016).

Table 2 shows the factor loadings of each item and the average variance extracted (AVE) of the constructs, which range between 0.58 and 0.80, exceeding the minimum required value of 0.50, as proposed in the studies by Fornell and Larcker (1981), demonstrating good convergent validity. It should be noted that the variable “BEH3” was removed from the analyses because it presented a low factor loading (<0.4).

Table 2

Average variance extracted (AVE).

Construct	Variables	Factor loadings	AVE
Attitude (ATT)	ATT1 - E-waste recycling is enjoyable	0.702	0.65
	ATT2 - Recycling electronic waste is responsible	0.913	
	ATT3 - E-waste recycling is good	0.93	
	ATT4 - E-waste recycling is beneficial	0.828	
	ATT5 - E-waste recycling is rewarding	0.691	
	ATI6 - Recycling electronic waste is sensible	0.73	
Subjective norms (SN)	SN1 - My friends expect me to recycle electronic waste	0.981	0.75
	SN2 - My work colleagues or study buddies expect me to recycle electronic waste	0.963	
	SN3 - The media influences me to recycle electronic waste	0.591	
Perceived behavioral control (PBC)	PBC1 - I know which e-waste items can be recycled	0.638	0.61
	PBC2 - I have many opportunities to recycle electronic waste	0.711	
	PBC3 - The government provides satisfactory resources for recycling electronic waste	0.72	
	PBC4 - I know where to take my electronic waste for recycling	0.929	
	PBC5 - I know how to recycle electronic waste	0.859	

Intention (INT)	INT1 - I intend to recycle electronic waste regularly	0.835	0.62
	INT2 - I plan to dispose of electronic waste at a nearby recycling station	0.842	
	INT3 - I plan to return the e-waste to the retailer or manufacturer	0.675	
Behavior (BEH)	BEH1 - I donate electronic waste	0.86	0.58
	BEH2 - I sell electronic waste	0.66	
Perceived severity (PES)	PES1 - The problem of environmental pollution caused by incorrect disposal of electronic waste is serious	0.815	0.79
	PES2 - When disposing of electronic waste, various harmful substances are generated	0.772	
	PES3 - Brazil is suffering from environmental pollution due to electronic waste waste problems	0.846	
	PES4 - Our surroundings are becoming increasingly polluted by electronic waste	0.896	
Perceived vulnerability (PEV)	PEV1 - Incorrect disposal of electronic waste will ultimately have a harmful effect on people	0.866	0.75
	PEV2 - When disposing of electronic waste incorrectly, several environmental risks are generated, which are harmful to health	0.91	
	PEV3 - The problem of incorrect disposal of electronic waste will eventually threaten our lives	0.81	
Response efficacy (REE)	REE1 - Efforts to reduce waste from electronic waste will help prevent environmental pollution	0.892	0.8
	REE2 - Efforts to reduce electronic waste are effective solutions to prevent environmental pollution	0.867	
	REE3 - If we try to reduce electronic waste waste, we can minimize environmental pollution	0.92	
Self-efficacy (SFE)	SFE1 - I can do enough to reduce e-waste waste	0.764	0.75
	SFE2 - I am confident that I will join in reducing e-waste waste	0.911	
	SFE3 - I will try to reduce electronic waste	0.863	

After the criterion of convergent validity was met, tests were conducted to demonstrate internal consistency (Cronbach's Alpha) and composite reliability. In this context, the minimum acceptable value for Cronbach's Alpha and composite reliability is generally 0.60, while values between 0.71 and 0.90 are considered satisfactory (Hair et al., 2009).

Table 3

Internal consistency and composite reliability of the constructs.

Construct	Cronbach's alpha	Composite reliability
Attitude	0.83	0.84
Subjective norms	0.81	0.89
Perceived behavioral control	0.84	0.87
Intention	0.77	0.78
Behavior	0.6	0.61
Perceived severity	0.79	0.83
Perceived vulnerability	0.8	0.87
Response efficacy	0.86	0.86
Self-efficacy	0.85	0.83

As shown in Table 3, the criteria established in the literature regarding internal consistency and composite reliability were considered satisfactory for the proposed model in the present study (Hair et al., 2009). Thus, the next step aimed to assess the discriminant validity of the SEM, understood as an indicator that the constructs or latent variables are independent of each other (Coelho et al., 2018). In the present study, cross loadings were analyzed, which are the indicators with higher factor loadings on their respective constructs than on others (Fornell & Larcker, 1981).

Table 4 shows the cross loadings of the observable variables that belong to the constructs previously presented in the methodology. Based on the obtained results, it can be inferred that the factor loadings of the observable variables on the original constructs are always higher than on others. Thus, it is evident that the proposed model in the present study has good discriminant validity based on Fornell and Larcker's (1981) criterion.

Table 4

Cross load values.

	Attitude	PBC	BEH	INT	SN	PES	PEV	REE	SFE
ATT1	0.692	-0.044	-0.077	0.212	0.117	0.285	0.266	0.300	0.228
ATT2	0.827	-0.052	-0.036	0.195	0.070	0.269	0.150	0.165	0.174
ATT3	0.833	-0.022	0.029	0.220	0.169	0.271	0.203	0.176	0.219
ATT4	0.714	-0.091	-0.078	0.139	-0.001	0.394	0.380	0.309	0.172
ATT5	0.680	0.065	0.057	0.212	0.185	0.319	0.206	0.232	0.192
ATT6	0.639	-0.125	-0.076	0.150	0.080	0.299	0.305	0.233	0.122
PBC1	0.056	0.698	0.222	0.264	0.304	0.105	0.124	0.048	0.223
PBC2	0.037	0.721	0.283	0.266	0.433	0.036	-0.050	-0.006	0.207
PBC3	-0.048	0.747	0.322	0.129	0.364	-0.089	-0.186	-0.137	0.013
PBC4	-0.082	0.879	0.436	0.317	0.366	-0.058	-0.069	-0.068	0.112
PBC5	-0.121	0.846	0.359	0.282	0.324	-0.078	-0.055	-0.070	0.104
BEH1	-0.024	0.372	0.856	0.327	0.270	0.085	0.071	0.062	0.248
BEH2	-0.029	0.359	0.809	0.165	0.139	-0.069	-0.120	-0.096	0.027
BEH3	-0.015	0.059	0.321	0.150	0.008	0.023	0.018	0.039	0.035
INT1	0.232	0.308	0.281	0.857	0.403	0.255	0.170	0.220	0.468
INT2	0.222	0.249	0.242	0.875	0.353	0.275	0.239	0.263	0.495
INT3	0.200	0.262	0.258	0.758	0.414	0.222	0.139	0.157	0.331
SN1	0.184	0.389	0.213	0.439	0.956	0.113	0.032	0.068	0.293
SN2	0.148	0.376	0.180	0.467	0.949	0.159	0.080	0.112	0.311
SN3	0.024	0.454	0.266	0.262	0.619	-0.083	-0.066	-0.054	0.050
PES1	0.365	-0.108	-0.085	0.218	-0.007	0.758	0.477	0.335	0.331
PES2	0.322	-0.136	-0.073	0.150	-0.059	0.619	0.452	0.330	0.214
PES3	0.323	0.055	0.080	0.292	0.176	0.865	0.499	0.416	0.362
PES4	0.303	0.025	0.086	0.258	0.124	0.865	0.609	0.446	0.383
PEV1	0.286	-0.048	0.039	0.231	0.027	0.534	0.911	0.393	0.313
PEV2	0.317	-0.149	-0.102	0.120	-0.015	0.562	0.792	0.451	0.289
PEV3	0.250	0.002	-0.018	0.182	0.059	0.573	0.828	0.442	0.322
REE1	0.294	-0.091	-0.007	0.245	0.042	0.394	0.454	0.871	0.429
REE2	0.262	-0.036	0.020	0.226	0.105	0.448	0.391	0.902	0.479
REE3	0.277	-0.033	-0.024	0.212	0.027	0.461	0.465	0.879	0.514
SFE1	0.185	0.146	0.074	0.383	0.161	0.358	0.266	0.515	0.792
SFE2	0.257	0.162	0.213	0.507	0.288	0.386	0.312	0.477	0.926
SFE3	0.219	0.122	0.150	0.459	0.264	0.351	0.362	0.411	0.875

macATT = Attitude; PBC = Perceveid behavioral control; INT = Intention; SN = Subjective norms; PES = Perceived severity; PEV = Perceived vulnerability; REE = Response efficacy; SFE = Self-efficacy

Given the satisfactory evaluation of reliability and validity in the measurement model, the identification of the structural model can proceed. The first step in estimating the structural model involved examining the fit results of the hypothetical model. Some common fit indices reported in structural equation modeling aim to identify the quality of the model fit. The common criteria for SEM were previously suggested, and a comparison between the results obtained in this research and the values recommended by the literature (Hair et al., 2009) is presented in Table 5.

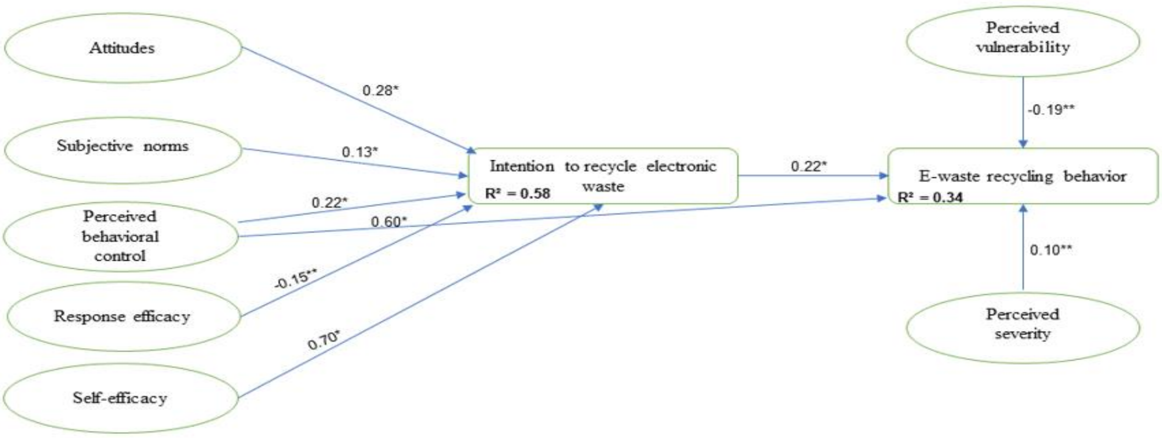
Table 5

Results of the adjustment model.

Fit index	Recommended criteria	Results in this study
TLI (Tucker Lewis Index)	> 0.9	0.988
GFI (Goodness of fit Index)	> 0.9	0.987
NFI (Bentler-Bonett Non-normed Fit Index)	> 0.9	0.981
CFI (Comparative Fit Index)	> 0.9	0.989
RFI (Bollen's Relative Fit Index)	>0.9	0.989
IFI (Bollen's Incremental Fit Index)	>0.9	0.989
RNI (Relative Noncentrality Index)	>0.9	0.994
RMSEA (Root Mean Square Error of Approximation)	< 0.06	0.059
Chi-square	-	910.326
Degrees of Freedom (DF)	-	404
Chi-square/DF	<3	2.25

Regarding the Chi-square value, there is no consensus in the literature on a cutoff point (Hair et al., 2009). However, it is emphasized that the ratio between Chi-square and Degrees of Freedom (Chi-square/DF) should be less than 3 (Hair et al., 2009). In the case of the tested model, the ratio between Chi-square and Degrees of Freedom was considered ideal, as a value of 2.25 was obtained. Finally, after confirming that the structural model meets the requirements proposed by the literature, the graphical representation of the adjusted model was carried out.

Figure 4
Adjusted structural model.



* = Statistically significant (p<0.05); ** = not significant (p>0.05);

The adjusted structural model, as illustrated in Figure 4, visually represents the relationships between the variables analyzed in the research. It can be inferred that the explained variance (R^2) for intention is 0.58 (58%) and 0.34 (34%) for electronic waste recycling behavior. After constructing the adjusted model, table 6 was created to summarize the results of the structural model and compare the theoretically grounded hypotheses in this study.

Table 6

Summary of research results.

Hypotheses	Direction of the relationship	Variance	P value	Result
H1: Attitude → Intention	+	0.4	<0.01	Hypothesis confirmed
H2 Subjective norms → Intention	+	0.29	<0.01	Hypothesis confirmed
H3: Perceived behavioral control → Intention	+	0.33	<0.01	Hypothesis confirmed
H4: Perceived behavioral control → Behavior	+	0.63	<0.01	Hypothesis confirmed
H5: Intention → Behavior	+	0.17	<0.05	Hypothesis confirmed
H6: Perceived vulnerability → Behavior	-	-0.19	>0.05	Hypothesis rejected
H7: Perceived severity → Behavior	+	0.1	>0.05	Hypothesis rejected
H8: Response efficacy → Intention	-	-0.15	>0.05	Hypothesis rejected
H9: Self-efficacy → Intention	+	0.7	<0.05	Hypothesis confirmed

Regarding H1, the present study found a significant and positive relationship between people's attitudes and the intention to recycle electronic waste. This relationship is also corroborated by the studies of Aboelmaged (2021). Additionally, it can be inferred that the respondents in the sample have a positive attitude toward electronic waste recycling. Finally, by demonstrating a statistically significant relationship between attitude and intention, this study confirms the findings of Li et al. (2019) in determining that attitude is the most influential factor in shaping individuals' intentions. It is also important to note that having a positive attitude toward the environment leads individuals to believe they are highly confident in their ability to adopt pro-environmental behaviors (Gkargkavouzi et al., 2019). Moreover, the confirmation of the hypothesis reinforces the relevance of attitude as a key factor in forming recycling intentions. This contributes to consolidating this relationship in the literature, strengthening the theoretical foundation in the field of sustainable behavior. Finally, private and public organizations can direct efforts to develop strategies that promote a positive attitude toward electronic waste recycling. These strategies may involve awareness campaigns, environmental education, and initiatives that demonstrate the benefits of recycling electronic waste (Echegaray & Hansstein, 2017; Parajuly et al., 2022).

Based on the results obtained, it can also be inferred that H2 and H3 were statistically confirmed. Thus, it is observed that subjective norms and perceived behavioral control are determinant factors preceding individuals' intentions regarding electronic waste recycling behavior. In other words, the influence of peers (colleagues, friends, relatives) and the perception of difficulties and/or the absence of barriers to recycling can positively influence people's intentions to recycle electronic waste. The results corroborate the evidence present in the studies by Echegaray and Hansstein (2017) and Borthakur and Govind (2018), indicating that subjective norms and perceived behavioral control have a positive influence on the intention to recycle waste. From an academic perspective, by corroborating the results of other authors, the present study contributes to the consistency and generalization of subjective norms and perceived behavioral control as direct psychosocial antecedents of the intention to recycle electronic waste. This may lead to a broader consensus on the importance of these factors.

Furthermore, based on the obtained results, from a managerial perspective, organizations and authorities can develop strategies to influence subjective norms, emphasizing the importance of electronic waste recycling through positive social influences. Finally, efforts can be directed towards removing perceived barriers, promoting perceived behavioral control (Aboelmaged, 2021).

Regarding H4 and H5, the results found that perceived behavioral control and behavioral intention positively and significantly precede electronic waste recycling behavior. Furthermore, the evidence suggests that perceived behavioral control (H4) carries more weight than recycling intention (H5) in explaining behavior. In this context, the importance of perceived behavioral control as the construct with the greatest impact on recycling behavior confirms that people need to feel they have control over their ability to recycle (Strydom, 2018). From an academic perspective, these results contribute to the enhancement of the TPB, highlighting that perceived behavioral control can be a stronger predictor of behavior than intention itself. This nuance can influence future applications of TPB-related hypotheses in the recycling context (Strydom, 2018). Finally, the dissemination of clear information about how materials are recycled and the positive impact this has on the environment can reinforce the perception of control (Mohamad et al., 2022; Strydom, 2018). In this way, understanding the process can reduce uncertainty and increase confidence in the ability to recycle effectively.

Regarding hypotheses H6 and H7, the research results diverge from the studies of Jang and Lee (2022), finding no statistically significant evidence that perceived vulnerability and perceived severity positively influence electronic waste recycling behavior. A possible explanation for this result is that there may be limitations in applying the PMT in the context of electronic waste recycling behavior. Thus, for the sample analyzed in this study, despite the descriptive data indicating a high perception that environmental threats can harm society, these factors are not sufficient for perceived vulnerability and perceived severity to exert a significant influence on recycling behavior as a form of protection against these threats. Finally, although H6 and H7 were rejected, this result aligns with other studies emphasizing that behavioral intention is one of the strongest direct predictors of pro-environmental behavior (Aboelmaged, 2021; Soomro et al., 2022; Strydom, 2018).

Regarding H8, the results indicated that response efficacy does not have a statistically significant influence on the intention to recycle electronic waste. This result is supported by the studies of Janmaimool (2017), which identified that response efficacy does not significantly influence the behavioral intention to recycle solid waste. Thus, the findings suggest that, from the PMT, the perception of response efficacy may not be a determining factor in the specific intention to recycle electronic waste, aligning with Janmaimool's (2017) previous research. This understanding highlights that the decision to recycle is complex, as many factors must be considered (Kothe et al., 2019).

Regarding H9, it can be inferred that self-efficacy has a positive influence on the intention to recycle electronic waste. Furthermore, as evidenced in Table 9, self-efficacy stands out as the main predictor of behavioral intention. This result suggests that people are more inclined to engage in electronic waste recycling when they have confidence in their own abilities to perform this task. In other words, the statistically positive influence of self-efficacy on behavioral intention suggests that many individuals show a positive predisposition to address the social problem associated with solid waste disposal (Mohamad et al., 2022). Additionally, this result supports the potential integration of the Protection Motivation Theory (PMT) with the Theory of Planned Behavior. Finally, understanding how self-efficacy relates to other psychosocial factors can enrich the understanding of behavioral determinants (Jang & Lee, 2022).

Based on the results presented in the adjusted structural model, where attitudes, subjective norms, perceived behavioral control, and self-efficacy explain 58% of the intention to recycle electronic waste, and intention along with perceived behavioral control explain 34% of the variance in electronic waste recycling behavior, this study offers stronger evidence compared to previous studies such as Borthakur and Govind (2018) and Mohamad et al. (2022). In both studies, these dimensions explained less than 50% of the variance in recycling intention. Additionally, these studies only evidenced 28% of the variance in recycling behavior. Furthermore, in agreement with previous research, such as Echegaray and Hansstein (2017), Strydom (2018), and Aboelmaged (2021), the finding that the explained variance (R^2) of recycling behavior is 34% in this study suggests the presence of external variables that may exert a direct influence on recycling behavior.

The results analyzed in this research are relevant for implementing programs that address the issue of electronic waste. Social marketing programs can help increase awareness and, consequently, individuals' recycling behavior (Ladeira et al., 2017; Salazar et al., 2019). The continuous increase in the volume of electronic waste disposal, along with inadequate waste management practices at the household level in developing economies, is attracting the attention of numerous stakeholders, including policymakers, NGOs, media, and academics (Echegaray & Hansstein, 2017). Therefore, it is crucial to identify the factors that influence individuals to effectively adopt a responsible approach, especially in less populated centers in countries like Brazil, where research and social actions related to the topic are still limited (Albuquerque et al., 2021).

5 FINAL CONSIDERATIONS

The present study aimed to investigate the factors that influence electronic waste recycling behavior. To this end, a theoretical review of the theories of planned behavior, protection motivation, and the topic of electronic waste was conducted, followed by data analysis using structural equation modeling. The research was classified as explanatory, descriptive, and quantitative. The results of the structural model indicated that attitude, subjective norms, perceived behavioral control, and self-efficacy positively and significantly influence the behavioral intention to recycle electronic waste. Thus, hypotheses H1, H2, H3, and H9 were empirically supported. Additionally, the results suggest that perceived behavioral control (H4) and behavioral intention (H5) positively and statistically significantly influence recycling behavior. In this regard, hypotheses H4 and H5 were also statistically supported. Therefore, the results achieved in this study have significant implications for the field of consumer behavior research, especially in the context of electronic waste. By investigating the factors that influence recycling behavior of this waste, the study contributes to a deeper understanding of the motivations and determinants behind consumer actions in this specific scenario.

Based on the results presented, the theoretical model proposed can serve as a solid foundation for future research in the field of electronic waste recycling. In this context, researchers can expand and refine the model, further exploring the interactions between the dimensions of the theory of Planned Behavior and protection motivation theory. It is also noteworthy that, within the context of the present research, based on the results obtained, perceived behavioral control emerges as the strongest direct predictor of electronic waste recycling behavior.

Finally, the results achieved provided theoretical and empirical support for the effects of the combination of TPB and PMT through a unique theoretical model in the context of electronic waste recycling. From this perspective, the structural model results demonstrated advances in understanding the determinants of electronic waste recycling behavior, as the explained variance (R^2) of intention and behavior was higher in the present research compared to other studies discussed in the results.

Based on the results obtained, the present study found the presence of external variables that may exert a direct influence on recycling behavior. One of the limitations of this study is associated with the exclusive inclusion of psychosocial variables as antecedents of recycling behavior. Another limitation concerns the consumer's difficulty in perceiving recycling possibilities for electronic waste. For future research, it is suggested to incorporate sociodemographic variables and other external factors (such as social marketing and infrastructure) that may, in turn, influence individuals' recycling behavior. Additionally, it is recommended to replicate the research in other cities in the Northeast, throughout Brazil, and globally, to analyze potential discrepancies between samples.

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